Worker-Side Discrimination: Beliefs and Preferences

- Evidence from an Information Experiment on Job-Seekers *‡

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Abstract

In this paper we provide novel evidence on the distribution of workers' preferences on manager's gender and their beliefs on manager's mentoring ability that impacts the workers' career. We design and conduct a within-worker information experiment and embed it in a hypothetical job choice survey for job-seekers and use it to estimate a job choice model with worker preferences and beliefs. In absence of information on manager quality, on average workers are indifferent between male and female managers. However, given information on manager mentorship, workers prefer to work for female managers–as exhibited by willing to receive 1.3-2.2% lower wages on average. Hence in the absence of additional information on manager mentorship, workers on average believe female managers have worse mentoring ability, valued at 1.6% of average annual wages. We find 60% of workers prefer to work for female managers, and in the absence of information on manager mentorship 62% believed male managers to be better mentors. We find policy relevant heterogeneity across maternal education and majors of workers. An ex-post survey where workers beliefs are directly elicited corroborate this finding.

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1 Introduction

Workers value non-pecuniary benefits of their jobs (Dey & Flinn (2005), Flory, Leibbrandt & List (2015), Blau & Kahn (2017), Mas & Pallais (2017), Sorkin (2018), Wiswall & Zafar (2018), Taber & Vejlin (2020)). Managers differ considerably in their ability to manage workers which directly impacts the careers of workers (Frederiksen, Kahn & Lange 2020). While mangers with high ability to manage workers have much lower attrition and turnover of their subordinate workers (Hoffman & Tadelis 2021), it remains an open question as to how the gender and ability of managers directly influences job-choice of workers.

Job choice of workers, especially job-ssekers–besides depending on their preferences–also depend on their beliefs (Robinson (1933), Conlon, Pilossoph, Wiswall & Zafar (2018), Jäger, Roth, Roussille & Schoefer (2021)) because they may not have complete information about their managers. Driven by their preferences and beliefs, suppose if workers do not want to work for females, then they would need to be paid a wage premium to work for female managers. In equilibrium, this could lower the rate at which females get hired or promoted to managerial positions thus generating glass-ceilings. Thus preferences and beliefs of workers become direct objects of interest given high turnover costs of replacing workers and retraining new workers, especially in tight labor markets.

In this paper we provide novel evidence on the distribution of workers' preferences on manager's gender and the distribution of worker beliefs on managerial ability. We define worker-side discrimination—in the spirit of a compensating differential (Rosen 1986)—as a form of selection, where individuals are willing to give up wages to work for their preferred managers in an otherwise identical job.[1] This willingness to trade off wages will be driven by their preferences on observable attributes and beliefs on unobservable attributes that they care about but do not have information on.

To identify preferences we follow the literature, and design and conduct a hypothetical job choice survey to ensure that demand side selection, labor market frictions and other omitted variables in general, do not confound our results (Blass, Lach & Manski (2010), Wiswall & Zafar (2018), Ameriks, Briggs, Caplin, Shapiro & Tonetti (2020), Fuster, Kaplan & Zafar (2021), Koşar, Ransom & Van der Klaauw (2021), Koşar, Şahin & Zafar (2021)).[2] Hypothetical choice methods are attractive because it can allow for unrestricted

[1] Becker (1971) conceptualized worker discrimination in the form of workers' dis-utility in working for specific group of employers. We extend the concept to incorporate worker beliefs and a tangible measure using compensating differentials in wages.

[2] Different workers may have different preferences on various dimensions of job attributes, many of which are unobservable to the econometrician. Such preferences are very difficult to isolate using data on realized job choices. Although data on realized job choices do have their own advantages, especially to

forms of preference heterogeneity (Blass, Lach & Manski 2010), while being able to hold attributes which are not a part of the survey as fixed through instructions (Wiswall & Zafar (2018), Koşar, Ransom & Van der Klaauw (2021), Koşar, Şahin & Zafar (2021)) and documented strong mapping between stated and actual choices (Mas & Pallais (2017), Wiswall & Zafar (2018), Parker & Souleles (2019)).

To identify beliefs we embed a novel within-worker information experiment where we exogenously vary observability of managerial ability. We conduct this hypothetical choice survey and the information experiment among job seeking students at a highly selective university who are one year away from graduating. We define managerial ability as the manager's mentorship quality motivated by a vast literature providing consistent evidence that mentorship has substantial positive impacts human capital accumulation (Falk, Kosse & Pinger 2020), wage expectations (Boneva, Buser, Falk, Kosse et al. 2021), productivity (Blau, Currie, Croson & Ginther 2010), promotion (Lyle & Smith 2014), workforce composition of firms, and can help minorities break through glass ceilings (Athey, Avery & Zemsky (2000), Müller-Itten & Öry (2021))[3]. We quantify mentorship of a manger as a rating on a five point scale, motivated by a recent trend of rating managers.[4]

We present respondents with twenty hypothetical job choice scenarios sequentially. In each choice scenario we ask respondents to choose one out of three jobs. We exogenously vary these jobs along realistic attributes (annual wages, flexible hours, manager's gender and manager mentorship quality) and cover the support of these attributes over the twenty different job choice scenarios.[5] In each scenario, respondents are asked to choose their most preferred job and then report the compensating differentials in wages—a nonparametric cardinal measure—that would make them indifferent between jobs.

Extracting beliefs on manager quality through direct elicitation could be difficult, especially if we worry that responses may be affected by social desirability bias. Hence within the hypothetical job choice scenarios we introduce a novel within-individual in-

understand employer discrimination. This is because employers on average care about a consistent set of attributes in their workers.

[3]In the same spirit of in-group mentoring, the American Economic Association's official mentoring program CeMENT has senior women faculty mentoring junior women faculty. See the AEA's dedicated webpage on mentoring here.

[4]Many firms like Google, e-Bay, Amazon collect anonymous surveys from employees where they are asked to rate their managers. Comparably, Completed, TheJobCrowd and Kunukunu are some of the notable start ups which provide ratings of managers and supervisors analogues to Glassdoor which provide firm ratings.

[5]Conceptually each hypothetical scenario could be thought of as a market. Choice in a market provides individual demand in that market. Choices over multiple scenarios, by varying attributes over their support allows us to trace out the individual demand curve. This generates panel data on choices and compensating differentials over the support of the job attributes which provides the identifying variation to estimate highly flexible models.

formation experiment where we exogenously vary observability of manager's mentorship. The information experiment works as follows. In the first ten job choice scenarios every individual observes three jobs in each scenario with attributes - annual wages, flexible hours and manager's name. As an attribute, mentorship is mentioned but the data is shown to be not available. We call these first ten scenarios "incomplete scenarios" throughout the rest of the paper, given that mentorship rating is not observable. In the last ten scenarios individuals observe jobs with all the above attributes including mentorship rating of the managers. We call these last ten scenarios "complete scenarios". We present an elaborate discussion on the key highlights of our design later in the paper.

We use our unique panel data on choices and compensating differentials to estimate a structural model of job choice where we estimate worker preference and belief parameters in monetary value–as willingness to give up wages. Identification is achieved as follows. Each worker forms expected utilities while choosing jobs. In the incomplete scenarios, workers implicitly form expectations on the mentorship rating because they do not observe it. Thus their responses are a function of both their preferences and their beliefs on mentorship conditional on other attributes. In contrast, in the complete scenarios, since individuals observe all attributes, their responses are a function of only their preferences. We instruct respondents in every scenario that jobs do not vary in attributes not mentioned in the survey (Wiswall & Zafar (2018), Koşar, Şahin & Zafar (2021), Koşar, Ransom & Van der Klaauw (2021)), and reported compensating differentials only increases wages without changing anything else about the job.[6] Thus variation in compensating differentials within complete scenarios identifies preferences. Variation in compensating differentials between complete and incomplete scenarios resulting from the information experiment isolates beliefs from preferences. The preference and belief parameters being identified for each worker, thus identifies the corresponding distributions.

We find that in the absence of information on manager mentorship — so that choices and compensating differentials are driven by *both preferences and beliefs* — workers are indifferent between male and female managers. However, with information on manager mentorship — so that choices and compensating differentials are driven by *only preferences* — workers prefer to work for female managers. On average, workers are willing to give up 1.7% of average annual wages to work for female managers. Hence, in the absence of information on manager quality, workers believed female managers to be worse mentors. We estimate these negative beliefs on female managers mentorship valued by

[6]This is one key advantage of using the hypothetical choice methodology over audit study field experiments. We also incorporate direct and indirect questions later in the survey to test how much theses instructions are followed.

workers on average at 1.6% of average annual wages. We do not find evidence of differences in average preferences and beliefs by the gender of the respondent unlike Flory, Leibbrandt & List (2015) and Wiswall & Zafar (2018). However, our within-worker information experiment reveals rich heterogeneity in the underlying distribution. Around 62% of individuals prefer to work for female managers. Approximately 60% of individuals believe female managers to be worse mentors than male managers in the absence of information on manager mentorship. We do not find evidence of negative beliefs on female manager mentorship among females majoring in Science and respondents whose mothers are more educated than their fathers.

As a robustness exercise, after respondents have responded to all the job choice scenarios, our survey further asks questions that directly elicit respondents' beliefs. Here we ask respondents to report their expected mentorship rating of managers in ten hypothetical jobs varying in manager names, flexible hours and annual wages. This allows us to corroborate the results on beliefs on manager mentorship from the information experiment in the job choice survey. Here too we find similar evidence of average negative beliefs regarding female manager mentorship as we found in the information experiment involving the twenty job scenarios. After going through all incomplete and complete choice scenarios, on average respondents still report negative beliefs on female manager mentorship when asked directly. This corroborating result tells us that individual responses in our information treatment which indirectly elicit their beliefs are potentially robust to social desirability biases.

Our paper contributes to multiple strands in the literature. First, to the best of our knowledge, this is the first paper known to us, to provide evidence on the distribution of preferences and beliefs of workers on manager's gender and mentorship.[7] While Flory, Leibbrandt & List (2015) find no evidence on the gender of the manager on application decisions, our analysis finds that this finding is sensitive to the information that workers have about these managers and there exist substantial underlying heterogeneity. Second, the literature on discrimination usually deals with discrimination driven by beliefs (statistical and biased beliefs) and those driven by preferences (taste-based) separately (Charles & Guryan (2008), Guryan & Charles (2013), Lang & Lehmann (2012), Bertrand & Duflo (2017)). To the best of our knowledge, this paper is the first to allow for discrimination

[7] Recent work by Abel (2019), Abel & Buchman (2020), have found that on average, individuals follow advice from male leaders, and providing information on the leader's experience and achievements makes them switch to follow advice of female leaders (Ayalew, Manian & Sheth 2021). Unlike the focus of this literature on manager's ability in the job, our focus is on the mentorship quality of managers motivated by evidence on significant impacts of manager's mentoring ability on labor market outcomes of their subordinate workers (Hoffman & Tadelis 2021) and the evidence on the Peter Principle–workers with high ability when promoted, do not translate into managers with high managerial ability (Benson, Li & Shue 2019).

driven by both beliefs and preferences and estimating their distributions. Our framework and unique panel data on compensating differentials allow us to not only test for statistical discrimination (Altonji & Pierret (2001), Lange (2007), Agan & Starr (2018), Bohren, Imas & Rosenberg (2019)),[8] but we can also quantify it as measures of willingness to give up wages.

Our next contribution is methodological. The literature using the stated-preference methodology estimates preference parameters in scenarios where individuals have information on all attributes of interest while keeping other attributes fixed in various objects of choice—electricity (Blass, Lach & Manski 2010), job attributes (Wiswall & Zafar 2018), location to migrate to (Koşar, Ransom & Van der Klaauw 2021), political candidate (Delavande & Manski 2015), insurance products (Boyer, De Donder, Fluet, Leroux & Michaud 2017). To this end, our paper is closest to Wiswall & Zafar (2018). We differ from this literature by asking for wage compensating differentials between jobs, instead of choice probabilities for each job. Given our design, compensating differentials allow us to jointly estimate the complete and incomplete scenarios to recover the distribution of preferences and beliefs without making additional distributional assumptions on the error terms of the job choice model. We can do this because the value of a dollar remains a dollar irrespective of whether the scenario is complete or incomplete.[9] This allows us to directly estimate and interpret preference and belief parameters as measures of willingness to give up wages.[10] Third, our question of interest involves identification of beliefs similar to Adams-Prassl & Andrew (2019). However we differ by indirectly eliciting beliefs with our information experiment, by using incomplete scenarios, thereby providing a new method of belief elicitation and estimation in settings where the researcher may worry that individuals may not report truthfully because of social desirability bias. Additionally we conduct an ex post direct belief elicitation to corroborate our results from the information experiment.

Another novel contribution of our paper is to quantify the demand for manager mentorship. we have consistent evidence on the positive impacts of mentorship and its duration on outcomes of mentees in academia, the corporate sector, the military and high

[8] Bohren, Imas & Rosenberg (2019) distinguish between discrimination resulting from correct beliefs (statistical discrimination) and those from incorrect beliefs. We can not take that route because we do not have access to data on the population distribution of mentorship quality which would provide the benchmark to test the hypothesis of biased beliefs.

[9] If we had asked for choice probabilities, we would need to additionally estimate the relative variances of the error terms in the complete and incomplete scenarios which would be identified from the relative variances of the choice probabilities in the complete and incomplete scenarios.

[10] Asking for compensating differentials is also advantageous from a stand-point of the cognitive load on the respondents, and consistency with how the model works in conjunction with the instructions given to the respondents.

schools (Athey, Avery & Zemsky (2000), Blau, Currie, Croson & Ginther (2010), Lyle & Smith (2014), Falk, Kosse & Pinger (2020), Müller-Itten & Öry (2021), Boneva, Buser, Falk, Kosse et al. (2021)). To the best of our knowledge, our paper provides the first estimates of the demand for high quality mentors in terms of the wages job-seekers are willing to give up to work for managers who are better mentors. We estimate individuals are willing to give up to 5.65% of average annual wages for one standard deviation increase in mentorship rating. This result is also important to interpret the beliefs on mentorship, when it is unobservable to workers. If workers would not have cared about mentorship, then any belief distribution could have rationalized the data, resulting in beliefs to be fundamentally unidentified. Our job choice model incorporates this feature.

Finally our work is also a part of the growing literature of online surveys and experiments involving information treatments to study beliefs (Wiswall & Zafar (2015), Kuziemko, Norton, Saez & Stantcheva (2015), Charité, Fisman & Kuziemko (2015), Bordalo, Coffman, Gennaioli & Shleifer (2016), Alesina, Miano & Stantcheva (2019), Boneva & Rauh (2018), Alesina & Stantcheva (2020), Stantcheva (2021), Alesina, Ferroni & Stantcheva (2021)).

The paper is organized as follows: Section 2 provides details on the hypothetical choice job choice survey, the information experiment, and highlights the important features of the design. Section 3 describes the sample and raw patterns in the data. Section 4 describes a job choice model on how worker preferences and beliefs drive their chocies and compensating differentials. Section 5 shows identification. Section 6 discusses estimation details and results. Section 7 presents the empirical distribution of beliefs and preferences and shows evidence on the underlying heterogeneity. Section 8 discusses validity of the estimates of the belief parameters and further robustness checks. Section 9 discusses potential avenues of future research. Section 10 concludes.

2 The hypothetical job choice survey and the information experiment

Our hypothetical job choice survey started with instructions to the respondents and had three broad sections - (1) twenty job choice and compensating differential *scenarios*, (2) direct belief elicitation and (3) demographic questions. The structure is schematically represented in Figure 1. Below we describe the design and purpose of each section in detail.

2.1 Instructions

The first part of the survey included definitions of the attributes of jobs shown to individuals in each job as shown in Figure 2. Next individuals were given instructions to the survey as shown in Figure 3. There were two key instructions. First, individuals were to assume that the jobs do not vary in any attribute not mentioned in the survey. Second, when asked to report the minimum increase in wages in unchosen jobs required to make them indifferent to their chosen job, individuals were to assume that this increase in wages would not change anything else about the job. After the instructions individuals were shown two example scenarios to get them acquainted before starting the main survey.

2.2 Job choice scenarios with compensating differentials

Each *scenario* had two questions - a choice among three hypothetical jobs, followed by a question on compensating differentials that will make respondents indifferent between jobs. The job attributes we exogenously varied were annual wages, availability of flexible hours, manager's name and manager's mentorship rating. The manager's mentorship rating–quantified on a five point scale–is described to the respondents as the average rating provided by the manager's current workers in an anonymous survey[11]. We varied the attributes subject to the restriction that no job in each scenario was strictly dominating. A total of 20 such scenarios were administered in the survey to cover the support of job attributes thus generating variation in reported compensating differentials which we use to identify and estimate our parameters of interest.[12] We embedded the information experiment as follows — for every respondent, although mentorship rating was mentioned as an attribute in all 20 scenarios, the first 10 scenarios (incomplete scenarios) did not have data on manager's mentorship, while the last 10 scenarios (complete scenarios) did. Examples of a complete and an incomplete scenario are shown in Table 2.

In every scenario, after a job was chosen, the following question was to report compensating differentials in the jobs that were not chosen. For each job that was not chosen, respondents were asked how much minimum increase in wages would they need in those jobs, so that they would choose them instead. This data provides us with wage compensating differentials that make the respondents indifferent between jobs. Individuals could

[11] This is motivated by the employee survey designs used in Amazon, Google and eBay

[12] Ideally we would want to vary job attributes along the full range of attributes, and thus would end up asking a large number of questions. However that would come at a cognitive cost to the respondents. Hence to strike a balance between cognitive load and substantial variation in job attributes we chose to administer 20 scenarios. This was mostly informed by our pilot surveys.

report this on a slider scale which ranged between 0 and 2 lakhs INR ($\approx$ 0 USD to 2857 USD). Individuals were told that if they needed more than 2 lakhs, they could max out the slider and another page would automatically appear asking them how much more they would need. Examples of job choice and compensating differential questions, in both an incomplete scenario and a complete scenario is shown in Table 3 and Table 4 respectively. Examples adapted to corresponding representative jobs in the USA are also shown in Table 5 and Table 6 respectively.

In the 20 scenarios there were 60 jobs, with half male and half female managers evenly distributed across the complete and the incomplete scenarios. Around half of the jobs had flexible hours and the other half did not. Average annual wages were 7 lakh INR ($\approx$ \$ 39,444 in PPP)[13] and the average rating of managers in the complete scenarios was 3.41. Table 7 shows summary statistics of attributes shown over the 60 jobs and Table 8 shows a balance of attributes across male and female managers.

2.3 Direct Belief Elicitation

This section of the survey directly elicited beliefs on manager mentorship. We designed this to corroborate results from estimating the job choice model with the data from the choice and compensating differential with complete and incomplete scenarios described above. In this section, individuals were presented with 10 jobs with the manager's name, annual wages and availability of flexible hours. Individuals were given a slider scale from zero to five and were asked to report their expected ratings in each job. This is shown in Figure 7.

2.4 Demographic questions

In this section we asked demographic questions to the respondents on their area of study (Arts, Science or Engineering), family income, parental education and occupation. Then individuals were asked questions which were specifically designed to infer whether individuals followed instructions or not. The survey ended with the choice of mode of online payment to complete the survey.

[13]This was the average wages of jobs that were offered to past cohorts. The variance in wages in the jobs we show was not too high. This mitigates any concerns that some jobs could be interpreted as entry-level jobs and some as senior level jobs. The attributes were varied such that no job in any scenario turned out to be strictly dominant.

2.5 Key Highlights of the Design

The design of the hypothetical job choice survey and the embedded information experiment enables us to identify beliefs and preferences from the reported choices and compensating differentials, given the instructions. In this section we explain some of the selected highlights of the design which help us to identify and flexibly estimate the parameters of our interest.

By construction, observing the entire choice set is one of the key advantages of our design. We observe which jobs are chosen and which jobs are not chosen. Additionally we also observe the compensating differentials that make individuals indifferent between all choices in the choice set. This gives us a non-parametric cardnial measure of utitlites and thus allows us to avoid making any distributional assumptions on the preference or the belief parameters. Data on compensating differentials which make individuals indifferent between jobs allows us to directly estimate and interpret parameters as measures of willingness to pay or willingness to give up wages.[14]

The information treatment is given to every individual. For each individual we observe a sequence of choices made and compensating differentials reported under the incomplete scenarios and then a sequence of choices made and compensating differentials reported over the complete scenarios. This allows us to uncover distributions of preferences and beliefs and not just the first moment if we had provided the information treatment to randomly chosen treatment group.

We collect data over twenty scenarios. We do this to cover as much of the support of the job attributes as feasibly possible. Concerns with potentially high cognitive load associated with making choices among large number of options makes it infeasible to ask individuals to choose among a large number jobs within each scenario. Hence we do this over a panel of scenarios making them choose and provide compensating differentials over three jobs per scenario. This generates a panel data on choices and compensating differentials over jobs which considerably vary in attributes.

The names of managers used in the survey were common names, directly indicative of gender. We used first names of managers only. In the Indian context last names can identify castes and religion. Since we only wanted to vary the gender dimension, we did not show any last names. This circumvents any potential concern that could arise because of differences in perceived gender roles between social classes. This is unlike in the USA wherein first names could be associated with both a race and a gender (e.g. Bertrand & Mullainathan (2004), **?**).

[14]This is also possible with data on choice probabilities, but requires an additional step to 'convert' the estimates to willingness to pay measures. See Wiswall & Zafar (2018).

3 Data

We collected data in the second week of April 2020 over 4 days, using an online survey[15] administered to students of a highly selective public university in India. Students eligible to participate in the survey were only those who were away from the job market by at most two years.[16] Upon completion of the survey, participants were paid INR 500 ($\approx$ \$24 in PPP[17]) through their preferred mode of online payment. See Appendix A.1 for further details on the administration and implementation of the online survey.

3.1 Selection and Description of Sample

The total number of participants in our survey was 604 out of which 591 completed the survey. Out of these we dropped 11 respondents who could either not be verified as students, or who completed the survey in less than 15 minutes, or both. The first percentile of duration to survey completion was at 13.89 minutes. The median time to survey completion was 51.37 minutes. Our final sample size for all our analyses is 580.

Table 9 reports sample descriptives. 41.72% of our sample consists of female students and the remaining 58.28% were male students.[18] 44% were enrolled in a department in the Arts faculty, 33.28% in Engineering and the remaining 22.07% were in Science. Female students were predominantly from Arts (67%). Males were predominantly from Engineering (49%) and Science (33%).

3.2 Patterns in the raw data

In this subsection we explore how individuals' choices and reported compensating differentials varied across the complete and the incomplete scenarios between jobs with male and female managers. This section is important before we give structure to rationalize the data in a framework involving preferences and beliefs. Table 10 reports the percent of jobs

[15] Access to internet was not a concern for students studying in a premier University in one of the largest metropolitan cities of India. However, we paid special attention in designing the survey to be mobile friendly, appreciating the fact a small but significant proportion of the target population may not have access to a computer.

[16] In 2020, total number of enrolled students in the university are 11,064. Out of them, 6,283 are enrolled in Undergraduate programs, 2,588 in Masters program and remaining 1,193 are enrolled in MPhil and PhD programs.

[17] 1 USD in 2019 purchasing power parity is equivalent to 21.07 INR. Source: `https://data.oecd.org/conversion/purchasing-power-parities-ppp.htm`

[18] In the survey we asked for the biological sex of the individual. We did not ask for the gender with which students would like to associate themselves, other than their biological sex.

chosen which had male managers and the percent of jobs chosen with female managers, in both the complete and the incomplete scenarios.

The first observation is that the percentage of jobs chosen with managers of both genders does not differ that much between male and female respondents. Furthermore we notice that in the absence of information on manager's mentorship (incomplete scenarios) the percent of jobs chosen with female managers were not that different from those with a male manager. However, in the complete scenarios, upon information revelation of manager mentorship, we observe that the percentage of chosen jobs with female managers is 61.1% which is around 20 percentage points higher than those with male managers.

Table 11 reports the average compensating differentials reported in unchosen jobs with male and female managers, and the difference between them along with the associated standard error and standardized difference. The table reports these numbers separately for the complete and the incomplete scenarios. In the absence of information on manager mentorship, we observe that individuals on average report higher compensating differentials to choose jobs with female managers than jobs with male managers, by 6.3 thousand INR ($\approx$ \$ 300). However this result flips in the complete scenarios. Individuals when provided information on the mentorship rating, on average demand 6.1 thousand INR ($\approx$ \$ 290) more in unchosen jobs with male managers. Both differences are statistically significant at the 99% level. We should maintain caution in interpreting these numbers because this compares compensating differentials among the set of jobs that they did not choose. Nevertheless, these numbers provide useful information on the set of unchosen jobs. In a world where individuals would have ranked jobs, these numbers suggest that in the complete scenarios, jobs with female managers would have been more likely to be ranked 2 but in the incomplete scenarios, would have been ranked last. The more informative way to understand the compensating differential data would be to compare attributes of the chosen and unchosen jobs, given the compensating differentials. This is what we do in the job choice model.

Before we delve into the model, we provide evidence for a natural question that arises in these contexts, on in-group preferences. In particular, are female respondents more likely to choose jobs with female managers.

3.3 Testing for In-group preferences

In this section we discuss whether females relative to males, are more likely to choose jobs with female managers. This can be answered with data from the complete scenarios using a difference-in-differences estimation strategy. We do not include the incomplete scenario data here, because we do not want to deal with omitted variable bias that will arise from how individuals form beliefs on mentorship which is unobserved to them in the incomplete scenarios.

Individuals are indexed by $i = 1, .., N$ and jobs by $j = 1, .., J$. Define $Choice_{ijs}$ as a binary variable taking value 1 if individual i in scenario s chose job j and 0 otherwise.

$$\begin{aligned} Choice_{ijs} = \delta_0 + \delta_1 \underbrace{\mathbb{I}(g_i = f)}_{\text{female worker}} \overbrace{\mathbb{I}(MG_{j(s)} = f)}^{\text{female manager}} + \delta_2 \underbrace{\mathbb{I}(g_i = f)}_{\text{female worker}} + \delta_3 \overbrace{\mathbb{I}(MG_{j(s)} = f)}^{\text{female manager}} \\ + Attributes'_{j(s)}\gamma_1 + Demographics'_i\gamma_2 + \lambda_s + e_{ijs} \end{aligned} \tag{1}$$

Respondent i's gender is denoted by g_i and gender of the manager in job j of scenario s is denoted by $MG_{j(s)}$. $Attributes_{j(s)}$ is the vector of job attributes associated with job j in scenario s, other than gender of the manager i.e., wages, flexible hours and mentorship of the manager. $Demographics_i$ is a vector of individual level demographics described in the previous section. Our specification controls for scenario fixed effects (λ_s) use the variation in choices made within scenarios resulting from the variation in attributes between choices within each scenario.

We estimate this difference-in-differences equation with a logit model. Table 12 shows the marginal effect estimates of equation (1). We find no evidence that females are more likely to choose jobs with female managers than males. Observe that we see this in the raw data as well, where we find no difference in choices or in compensating differentials across male and female respondents in both the complete and the incomplete scenarios. We will see this again when we present estimates of preferences and beliefs in the job choice model, by the gender of the respondent. As one would expect, higher wages, availability of flexible hours and better mentors are associated with higher likelihood of the jobs being chosen.

We now move on to describe and estimate a job choice model to unwrap this evidence of jobs with female managers being chosen more on average, through the lens of preferences of individuals and how beliefs operate in the absence of information on the manager's rating.

4 Model

In order to understand how preferences and beliefs play a role in job choices and compensating differential, we use a simple job choice model. We first explain how the model works in the complete scenarios and then in the incomplete scenarios.

Individuals are indexed by $i \in \{1, \ldots, N\}$ and jobs are indexed by $j \in \{1, \ldots, J\}$. Let X_j denote a K-dimensional vector of attributes of job j, over which individuals have preferences. The utility of an individual i from job j is given by

$$U_{ij} = u_i(X_j) + \epsilon_{ij},$$

where ϵ_{ij} are all unobservables that affect the utility of individual i from job j.

Individuals have preferences over the set of attributes $X = \{G, W, H, R\}$. They denote the indicator for a male manager, annual wages, availability of flexible hours and mentorship rating of the manager respectively.[19] In the complete scenarios respondents observe X for each job. In the incomplete scenario respondents observe $\tilde{X}$ where $\tilde{X} \equiv X \setminus R$. Individuals form expected utilities while reporting their job choice and corresponding compensating differentials that make them indifferent between jobs in expectation. In the incomplete scenarios when individuals do not observe mentorship rating R they use their beliefs on R given $\tilde{X}$ to fomr their expected utilities.

The model is non-parametrically identified upto the distribution of ϵ_i as shown in Appendix A.2. In the following sections to keep things simple, we use a linearly separable model. This functional form has no bearing on the identification of the parameter or its distribution, except for additive separability of the error terms ϵ_{ij}. Utility of an individual i, with preference parameter vector $\beta_i \in \mathbb{R}^K$ from job j with k-dimensions of attributes X_j is given by

$$U_{ij} = X_j' \beta_i + \epsilon_{ij} \tag{2}$$

4.1 Complete Scenarios

In the complete scenarios individuals observe all attributes in set X for each job. The expected utility of individual i from job j conditional on its observable attributes in the complete scenarios is given by

$$\mathbb{E}_i[U_{ij}|X_j] = \sum_{x \in X} \beta_i^x x_j + \mathbb{E}_i(\epsilon_{ij}|X_j) \tag{3}$$

We assume that all individuals know their preferences and hence do not take expectations over them. As explained above, this draws a clear parallel with asking for choices

[19] In this model an individual directly cares about the mentorship of the manager. In the Appendix we write and discuss identification of a more generic model in which the mentorship rating of the manager is taken as a signal of overall manager quality.

instead of choice probabilities.

4.2 Incomplete scenarios:

In the incomplete scenarios the rating of the manager is mentioned but the data is shown to be unavailable to the respondents. Hence, respondents form expectations over it in reporting their choices and compensating differentials. Denote the set of observable attributes in job j as $\tilde{X}_j \equiv X_j \setminus \{R_j\}$ in the incomplete scenarios. The expected utility of individual i from job j conditional on its observable attributes $\tilde{X}_j$ in incomplete scenarios is given by

$$\mathbb{E}_i[U_{ij}|\tilde{X}_j] = \sum_{x \in \tilde{X}} \beta_i^x x_j + \mathbb{E}_i(\beta_i^R R_j + \epsilon_{ij}|\tilde{X}_j) \tag{4}$$

To proceed we parameterize beliefs conditional on observables. Again to keep things simple we will specify the process of beliefs linearly. We revisit this specification later and consider alternatives when we interpret how beliefs about managers' ratings differ by the managers' gender.

$$\mathbb{E}_i(R_j|\tilde{X}_j) = \sum_{x \in \tilde{X}} \alpha_i^x x_j + \mathbb{E}_i(\eta_{ij}|\tilde{X}_j) \tag{5}$$

Observe that $\alpha_i^G = \mathbb{E}_i(R_j|G_j = male, W_j, H_j) - \mathbb{E}_i(R_j|G_j = female, W_j, H_j)$ represents how much on average individual i believes a male manager's mentorship rating differs from that of a female manager. Simplifying, the expected utilities in the incomplete scenarios are given by

$$\mathbb{E}_i[U_{ij}|\tilde{X}_j] = \sum_{x \in \tilde{X}} (\beta_i^x + \beta_i^R \alpha_i^x) x_j + \mathbb{E}_i(\epsilon_{ij} + \beta_i^R \eta_{ij}|\tilde{X}_j) \tag{6}$$

4.2.1 Discussion on model: Choices and Compensating differentials versus Choice probabilities

The literature in hypothetical choice methodology has focused primarily on asking for the respondent's probability of choosing each alternative within each scenario. Asking for probabilities make sense when individuals are asked about future choices with revelation of relevant information in between. The difficulty is that interpretation of the role of unobservables in this setting, could be made in one of two possible ways. Asking for probabilities imply resolution of resolvable uncertainty (Blass, Lach & Manski 2010). The uncertainty could arise from individuals learning about their preferences over time

(Delavande & Manski 2015).[20] But it is at odds with how the model operates, where it is taken as given that individuals know their preferences and the unobservables are interpreted as preference shocks. Thus it is not clear what individuals are understanding when they are being instructed to consider the attributes mentioned in the survey to be the only attributes along which the jobs vary.

To maintain clarity on the role of unobservables, we ask for one job choice among three options in each scenario, followed by a compensating differential to make individuals indifferent between jobs. This provides a clear parallel between the instructions provided and how the unobservables are modeled. Given the instructions provided in our setting - unobservables do not vary across jobs within scenarios, conditional on observables. Additionally asking for choices is more straightforward than probabilities and thus more appealing with respect to reducing cognitive load on respondents.[21]

5 Identification

In this section we show how our experimental panel data on choices and compensating differentials identify preference and belief parameters of our model of job choice by exploiting variation in reported compensating differentials within and between the complete and the incomplete scenarios. [22] As shown in Appendix Figure 3, individuals were instructed to assume that,

> **Assumption 1:** All attributes which are not mentioned in the survey are the same for all jobs.
>
> **Assumption 2:** Reported compensating differential only increases wages and changes nothing else about the job.

Observe that instruction 1 is an assumption between jobs, while instruction 2 is for within jobs. The purpose of these instructions was to ensure that there is no selection on attributes which are not mentioned in the survey. Wiswall & Zafar (2018) delineate the importance of this assumption (1) in contrast to audit and correspondence studies, where

[20]In Delavande & Manski (2015) voting behavior today could potentially be different from voting behavior in the future, if the individual learns about their preferences over time prior to the time of vote.

[21]We administered pilots where we asked for probabilities of choosing each job. Debriefs revealed individuals spent longer times in understanding or calculating probabilities. Time data revealed individuals spent a long time on the pages which included a primer in probabilities and probability examples, thus adding to our concern about cognitive load.

[22]In the Appendix we also write down a more flexible model where the rating variable is used as a signal for overall manager quality and show identification in that setting.

there is no control on employers to not assume anything else conditional on observables.[23] For both scenarios, assumption (2) implies that the compensating differential only increases the wage and does not change the conditional expectation of the unobservables. Note that for the incomplete scenarios, it applies to the conditional expectation of the rating of the manager as well.[24] We use the data on compensating differentials to equate expected utilities in the complete and the incomplete scenarios. These two assumptions, which form a clear parallel to the instructions given to the respondents, form the basis of our identification.

5.1 Preferences

In this section we show identification of the preference parameters β^x for all $x \in \{G, H, R\}$. The parameter of interest is β^G which is the preference for male managers. We use assumptions (1) and (2) to identify preferences using variation in compensating differentials within the complete scenarios. **Implication of Assumption (1):**
The instructions imply that unobservables across different jobs in conditional expectations are the same within each scenario. For every individual i and every job $j \neq k$ within each complete scenario,

$$\mathbb{E}_i(\epsilon_{ij}|X_j) = \mathbb{E}_i(\epsilon_{ik}|X_k)$$

Implication of Assumption (2):
In the complete scenarios, for each job k, individuals observe the vector of attributes $X_k = \{G_k, H_k, W_k, R_k\}$. Suppose individual i chose job j and then provided a compensating differential of Δ_{ijk} in order to choose job k instead. The instructions imply that for unchosen jobs like job k,

$$\mathbb{E}_i(\epsilon_{ik}|X_k, \Delta_{ijk}) = \mathbb{E}_i(\epsilon_{ik}|X_k) \tag{7}$$

Given the above, equating expected utilities between job j and job k with provided

[23]For more on audit studies in detecting discrimination see Heckman (1998) and related papers within it.
[24]Note that for the incomplete scenarios, the rating variable was mentioned but there were no rating available for each manager. we also had to make sure that neither do we prime individuals to think that the rating is indeed different across managers, nor do we make them assume that rating is the same across all managers. To achieve this, we used the following wording: *"Rating of each manager could be different, but the data is not available*, as shown in Table 2.

compensating differential of Δ_{ijk} and normalizing $\beta_i^W = 1$, we have,

$$\begin{aligned} \mathbb{E}_i(U_{ij}|X_j) &= \mathbb{E}_i(U_{ik}|X_k, \Delta_{ijk}) \\ \Delta_{ijk} &= \sum_{x \in X} \beta_i^x (x_j - x_k) \end{aligned} \tag{8}$$

Thus preference parameters β_i^x are identified using variation in reported compensating differentials in the complete scenarios under assumptions (1) and (2) for all $x \in X$

5.2 Beliefs

Now we turn to the incomplete scenarios in conjunction with the complete scenarios and show identification of the belief parameter α, exploiting the variation between the reported compensating differentials between the complete and the incomplete scenarios.

Implication of Assumption (1):

The instruction implies that unobservables affecting utilities and beliefs, across different jobs in conditional expectations are the same within each scenario. For every individual i and every job $j \neq k$ within each incomplete scenario,

$$\begin{aligned} \mathbb{E}_i(\epsilon_{ij}|\tilde{X}_j) &= \mathbb{E}_i(\epsilon_{ik}|\tilde{X}_k) \\ \mathbb{E}_i(\eta_{ij}|\tilde{X}_j) &= \mathbb{E}_i(\eta_{ik}|\tilde{X}_k) \end{aligned}$$

Implication of Assumption (2):

In the incomplete scenarios, for each job k, individuals observe the vector of attributes $\tilde{X}_k = \{G_k, H_k, W_k\}$. Suppose individual i chose job j and provided a compensating differential of $\tilde{\Delta}_{ijk}$ in order to choose job k instead. All that the compensating differential does is that it increases the wages in job k by $\tilde{\Delta}_{ijk}$. The implication of Assumption (2) is that it has no effect on the conditional expectation of managers' ratings or on the conditional expectation of the unobservables affecting utility. That is,

$$\begin{aligned} \mathbb{E}_i(R_k|\tilde{X}_k, \tilde{\Delta}_{ijk}) &= \mathbb{E}_i(R_k|\tilde{X}_k) \\ \text{and} \quad \mathbb{E}_i(\epsilon_{ik}|\tilde{X}_k, \tilde{\Delta}_{ijk}) &= \mathbb{E}_i(\epsilon_{ik}|\tilde{X}_k) \end{aligned} \tag{9}$$

Thus the expected utility from job k taking into account the compensating differential of $\tilde{\Delta}_{ijk}$ is :

$$\begin{aligned}
&\mathbb{E}_i(U_{ik}|\tilde{X}_k, \tilde{\Delta}_{ijk}) \\
&= \beta_i^G G_k + \beta_i^H H_k + \beta_i^W (W_k + \tilde{\Delta}_{ijk}) + \beta_i^R \mathbb{E}_i(R_k|\tilde{X}_k, \tilde{\Delta}_{ijk}) + \mathbb{E}_i(\epsilon_{ik}|\tilde{X}_k, \tilde{\Delta}_{ijk}) \\
&= \beta_i^G G_k + \beta_i^H H_k + \beta_i^W (W_k + \Delta_{ijk}) + \beta_i^R \mathbb{E}_i(R_k|\tilde{X}_k) + \mathbb{E}_i(\epsilon_{ik}|\tilde{X}_k) \\
&= \sum_{x \in \tilde{X}} (\beta_i^x + \beta_i^R \alpha_i^x) x_k + \beta_i^W \tilde{\Delta}_{ijk} + \mathbb{E}_i(\epsilon_{ik} + \beta_i^R \eta_{ik}|\tilde{X}_k)
\end{aligned} \tag{10}$$

given that beliefs about ratings are modeled as in (5).
Individuals are assumed to know their preference parameters and hence do not take expectations over them. Equating expected utilities between job j and job k with provided compensating differential of $\tilde{\Delta}_{ijk}$ and as before normalizing $\beta_i^W = 1$ under A1, we have

$$\begin{aligned}
\mathbb{E}_i(U_{ij}|\tilde{X}_j) &= \mathbb{E}_i(U_{ik}|\tilde{X}_k, \tilde{\Delta}_{ijk}) \\
\tilde{\Delta}_{ijk} &= \sum_{x \in \tilde{X}} \underbrace{(\beta_i^x + \beta_i^R \alpha_i^x)}_{\tilde{\beta}_i^x} (x_j - x_k)
\end{aligned} \tag{11}$$

Now identification of α is straightforward. We know that, for each attribute $x \in \tilde{X}$

$$\tilde{\beta}_i^x = \beta_i^x + \beta_i^R \alpha_i^x \tag{12}$$

Observe that $\tilde{\beta}^x$ is comprised of two terms: the preference parameter for attribute x and how much x affects the belief about manager's rating, given that the individual cares about manager's rating.

Thus given identification of β_i^x and $\tilde{\beta}_i^x$, we have for all $x \in \tilde{X}$

$$\alpha_i^x = \frac{\tilde{\beta}_i^x - \beta_i^x}{\beta_i^R} \tag{13}$$

Thus α_i^x are identified $\forall x \in \tilde{X}$ as long as $\beta_i^R \neq 0$

We want to end this section with a small discussion on the intuitive difference between the two sets of equations on compensating differentials in the complete and in the incomplete scenarios. In the complete scenarios, the compensating differentials are a function of how do jobs j and k vary in their attributes, weighted by how much individual i cares about each of those attribute. In contrast, in the incomplete scenarios, they are weighted by not only how much individuals care about each attribute, but also with how much they believe each attribute is correlated with mentorship and how it differs between jobs j and k in each of the incomplete scenarios.

Additionally note that there are two circumstances when beleifs are not identified. Observe that α_i^x is not identified if $\beta_i^R = 0$ i.e. when i does not care about mentorship. The underlying intuition is that if individuals do not care about mentorship of managers, then any belief distribution can rationalize the observed data. This is because the variation in the observed choices and compensating differentials are independent of mentorship. Secondly beleifs are not identified if individuals believe mentorship is independent of all observed attributes. In particular, in that case we will have for each individual i, $\mathbb{E}_i(R_k|\tilde{X}_k) = \mathbb{E}_i(R_k)$ for all jobs k which is a constant, though it could vary by i. But importnatly it does not vary with the observed attributes, so any variation in observed attribute by construction cannot be used to identify beliefs.

6 Estimation

We use variation in the reported compensating differentials to estimate the preference and belief parameters of our model. The compensating differentials are reported with two different but independent measurement errors. One measurement error results from reporting compensating differentials in multiples of five as shown in Figure 4. This is also observed in surveys asking for choice probabilities (Blass, Lach & Manski 2010). The second type of measurement error arises from the design of the survey. Individuals had a slider to report compensating differentials and sliding the slider could cause some random measurement error, even though individuals could see the exact amount as they slid the slider. Both types of measurement errors are classical in nature and will only inflate standard errors. Consistency of the estimates is not affected. Denote Δ_{ijk}^* and $\tilde{\Delta}_{ijk}^*$ as the latent compensating differentials and e_i and $\tilde{e}_i$ as the composite classical measurement errors in the complete and the incomplete scenarios respectively. Thus we have the following set of estimating equations for each individual i and each pair of jobs j and k within every scenarios:

$$\begin{aligned} \Delta_{ijk}^* &= \sum_{x \in X} \beta_i^x (x_j - x_k) + e_i \\ \tilde{\Delta}_{ijk}^* &= \sum_{x \in \tilde{X}} (\beta_i^x + \beta_i^R \alpha_i^x)(x_j - x_k) + \tilde{e}_i \end{aligned} \tag{14}$$

With classical measurement errors, we have,

$$\begin{aligned}\mathbb{E}[\Delta^*_{ijk}|X_j, X_k] &= \sum_{x\in X} \beta^x_i (x_j - x_k) = (X_j - X_k)'\beta_i \\ \mathbb{E}[\tilde{\Delta}^*_{ijk}|\tilde{X}_j, \tilde{X}_k] &= \sum_{x\in \tilde{X}} (\beta^x_i + \beta^R_i \alpha^x_i)(x_j - x_k) = (\tilde{X}_j - \tilde{X}_k)'\tilde{\beta}_i\end{aligned} \tag{15}$$

We jointly estimate the above system of equations (14) using constrained least squares where we normalize the preference parameter on wages to one ($\beta^W_i = 1$). By construction, the estimating equations have no constant since they are derived by equating utility functions. We use the the block bootstrapap at the respondent level to allow for arbitrary correlation among responses within each respondent. We describes the details of the joint estimation and the bootstrap algorithm in Appendix A.3

6.1 Model Estimates

In this section we discuss the estimates of the preference and belief parameters of the job choice model described in the previous section. In the first subsection we discuss estimates for preference parameters focusing on the preference on the gender of the manager. Next we discuss preference and thus demand for good mentors. We discuss estimates of the belief parameters focusing on beliefs on mentorship by the gender of the manager in the final subsection. This order of discussion is natural because only after having an understanding of how much individuals care about the gender and the mentorship of the manager, is it useful to discuss beliefs on mentorship by gender of the manager. Since the utility parameter on wages is normalized to 1, and wages are in hundred thousand (lakh) INR, the estimates should be interpreted as valuations of each attribute in hundred thousand INR.[25] For better interpretability we also present these estimates by converting them to percent of average annual wages.

6.1.1 Preference to work for female managers

Table 13 shows estimates of equation system (14) representing indifferences in the complete and incomplete scenarios jointly exploiting variation in reported compensating differentials across jobs with exogenously varying attributes. We first discuss the complete scenarios under which are the pure preference parameter estimates on manager's gender, flexible hours and average rating of the manager's mentorship.

[25] Alongside we present the purchasing power parity equivalent in USD.

The most striking result is the evidence of a strong preference to work for female managers as shown in the panel of complete scenarios. The preference parameter for male managers (β^G) is negative and statistically significant. On average, individuals are willing to give up 12 thousand INR ($\approx$ \$570) to work for a female manager. This value corresponds to 1.7% of average annual wages. The 95% confidence interval of this value as a percent of average annual wages is from 1.3% to 2.2%.[26]

For the incomplete scenarios, the 'biased' estimate of preference for male managers ($\tilde{\beta}^G$) is statistically indistinguishable from zero. The difference in the estimates across the complete (β^G) and the incomplete scenarios ($\tilde{\beta}^G$), provides evidence that in the absence of information on the mentorship quality of managers, individuals believe that male managers are better mentors. The results suggest that beliefs and preferences are operating in opposite directions to generate such estimates. This difference in the estimates between the complete and incomplete scenarios is evidence of statistical discrimination against female managers if and only if individuals prefer to work for managers who are better mentors. We now turn to discussing preferences on the mentorship attribute. As explained earlier in the identification section, if individuals do not care about manager's mentorship (i.e. $\beta^R = 0$) then beliefs are fundamentally unidentified and as such this difference cannot be taken as evidence of statistical discrimination.

6.1.2 Demand for mentorship quality in Managers

Table 13 shows clear evidence of respondents caring about high quality mentorship in their managers. Individuals on average are willing to give up around 80 thousand INR ($\approx$ \$ 3,800) or 11% of their average annual wages to work for a mentor who ranks one point higher on a five point scale. Converting it to standard deviation units, given the variation in mentorship rating in the scenarios presented to the respondent, one standard deviation increase in mentorship is valued at 5.65% of average annual wages. This estimate could seem large at first glance. However, they are not surprising given that the respondents are job-seekers who are about to enter the labor market for the first time. Under diminishing returns to mentorship, a marginal increase in mentorship is of much higher value to first time job seekers than experienced workers in the labor market. Additional descriptive evidence on individuals caring for mentorship is presented in Appendix A.4

A potential concern could revolve around how respondents interpret average mentorship quality if the respondent is very different from the current workers. In such a case,

[26] Bias corrected bootstrap confidence interval.

the mentorship variable could be uninformative to the respondent.[27, 28] Even though our scenarios in the survey does not go into the specifics of types of jobs or industry to reduce cognitive load, if respondents were indeed thinking of jobs dominated by out-group workers, such that mentorship quality is uninformative, then we would have seen its evidence in the data. On the contrary, the lower bound of the 95% confidence interval on preference for high rated mentors is at 10.5% of average annual wages, far away from zero.[29]

6.1.3 Beliefs

The estimates of the belief parameter on male manager's mentorship (α^G) are obtained from estimates of the vectors $(\tilde{\beta}^G, \beta^G, \beta^R)$ using equation (13). The first row of Table 14 shows that on average male managers are believed to have higher mentorship rating by 0.14 points (on a 5 point scale) or by 0.28 standard deviations than female managers. Classical measurement error in the reported compensating differentials leading to inflation of standard errors in the estimation of preference parameters will trickle down to the standard errors of the belief parameters. In spite of that the belief parameter estimate is statistically significant. The estimates in conjunction with the model and evidence that mentorship is a highly sought after manager attribute, imply that in the absence of a manager's rating, both genders believe that male managers are better mentors than female managers.

The estimates of α^G are hard to interpret since they represent relative beliefs on a five point scale. A more interpretable measure of beliefs–in monetary terms–is the valuations of beliefs on male manager mentorship ($\beta^R \alpha^G$). In Table 15 we report these estimates of the valuation of the worker beliefs. Observe that the difference in the parameters between the complete and the incomplete scenarios provides us exactly that. $\tilde{\beta}^x - \beta^x = \beta^R \alpha^x$ for all $x \in \{G, W, H\}$. Thus estimates of $\beta^R \alpha^G$ provides us an estimate of the valuation of statistical discrimination.[30]

[27] Recall mentorship rating was presented in the survey as the average mentorship rating of the manager provided by its current workers.

[28] An example could be a female getting a job offer from the construction sector which is heavily male dependent

[29] There is less concern about other interpretations of mentorship. For example, it is unlikely that an English major would be answering questions by invoking upon themselves the extra cognitive load to think about jobs outside of their domain of specialties.

[30] Also note that $\frac{\mathbb{E}(\tilde{\beta^G}_i - \beta_i^G)}{\mathbb{E}(\beta_i^R)} \neq \mathbb{E}(\frac{\tilde{\beta^G}_i - \beta_i^G}{\beta_i^R}) = \mathbb{E}(\alpha_i^G)$. But $\mathbb{E}(\tilde{\beta^G}_i - \beta_i^G) = \mathbb{E}(\beta_i^R \alpha_i^G)$ provides us the average valuations of beliefs.

7 Heterogeneity

7.1 Distributions

Each respondent in our survey answered questions in 20 scenarios with 3 jobs each. This gives us 40 unique data points of compensating differentials across jobs of varying attributes for each respondent - 20 from the incomplete and 20 from the complete scenarios. We use these data to estimate the model for each individual separately. Using the empirical distribution of respondent specific estimates we can compute the sample mean preferences and given the standard deviation we can compute standard errors of the mean. But more interestingly, using the empirical distributions we carry out two informative exercises. First, we quantify the proportion of individuals who statistically discriminate against female managers. Second, we regress the estimated parameters on sample characteristics to obtain the correlations between discrimination and observed characteristics.[31] The second exercise in itself is also a simple test of preference homogeneity.[32] We also address the concern that individual parameters may be estimated with noise and discuss bounds on the estimates under reasonable assumptions. For better interpretability of the figures we have converted the preference and belief parameters into percent of average annual wages.

As shown in Figure 5 the empirical CDF reveals that 60% of respondents in absence of information on manager quality believe female managers to be of worse quality . If the true underlying distributions of preferences, beliefs and noise are symmetric then this number is a lower bound on the proportion of individuals who statistically discriminate against female managers. This is because under symmetry the median is unaffected and hence the true cumulative distribution will intersect zero at a lower point than what we see in Figure 5. Upon comparison of the estimate of the mean and its standard error obtained by estimating the model for each respondent with the base model with all respondents together, we find that they are very close. Hence even though individual estimates could be noisy, this would not have been observed had the noise on average not been zero. Similarly in Figure 6 we observe that individuals' preferences upon receiving information on manager quality reveals that at least 62% of individuals prefer working

[31] The parameter estimates which we regress on observed demographics could be noisy, being estimated from 40 observations. This will overstate the standard errors of the regression coefficients. Finding statistically significant estimates, in spite of overstated standard errors makes an even stronger case for heterogeneity.

[32] One could also take the route of testing for heterogeneity using wild bootstrap-*t* (Cameron, Gelbach & Miller (2008), Busso, Gregory & Kline (2013)). However in our case, the test is non-standard since it is testing at the boundary of the parameter space- testing the null hypothesis of zero variance against the alternative hypothesis of positive variance.

for female managers. Also it is important to note that it is not everyone who prefers to work for a female manager, even though on average we find a preference to work for female managers. The distribution reveals two important points. First, there are more individuals who prefer working for female managers. Second, the amount of money that would make an individual who prefers to work for a female manager switch to working for a male manager is higher than the amount needed to make an individual preferring to work for a male manager switch and work for a female manager.

7.2 By Gender of Respondent

In this section we present results by running the model separately for male and female respondents. We find that preferences on male managers (β^G) and beliefs on mentorship of male managers ($\beta^R \alpha^G$) on average are not statistically different between male and female respondents. But it is important to note that we do see economically lower statistical discrimination against female managers among female respondents relative to male respondents.

7.3 By Field of study

In this section we delve further and present results where we estimate the model separately for respondents enrolled in different fields of study - Arts, Science and Engineering. Since sample runs small here, normal based confidence intervals may not be reliable (Hansen 2021). Thus, for inference we use bias-corrected bootstrap confidence interval. In Table 17 we find that preferences and beliefs do not differ between Arts and Engineering. However respondents majoring in Science have lower statistical discrimination against female managers.

7.4 By Gender of Respondent and Field of study

To further investigate the result of lower statistical discrimination in Science majors, we run the model by the field of the study and the gender of the respondents in Table 18. We find that this result is driven by females in Science. In Table 18 we find no evidence of statistical discrimination towards female managers by female respondents who are enrolled in Science majors. Additionally among respondents majoring in Arts, we find that males are more than twice as statistically discriminatory as female respondents. Also among males, we find that statistical discrimination against female managers is the highest among males enrolled in Arts. Females in Engineering value mentorship rating at

7.4% of average annual wages which is the lowest among other gender-department pairs. However the standard error on this estimate is relatively much higher (it is in between three to five times as high as the standard errors on the estimates from other groups). This is potentially driven by very few females enrolled in Engineering departments (only about 10% of females in our sample are Engineering majors).

7.5 By Parental Education

In this section we estimate the model for two subsamples defined by relative parental education. In particular we estimate the model for respondents whose mothers are more educated than their fathers and vice versa. Our sample has 13% of individuals whose mothers are strictly more educated than their fathers. Table 19 reports estimates of the preference and belief parameters. For the subsample whose mothers are more educated than their fathers, we do not find evidence of statistical discrimination against female managers. The results do not change if we introduce another subsample whose mothers and fathers are equally educated.

8 Robustness

8.1 Validity of estimates of the belief parameter

In the penultimate section of the survey we directly elicit beliefs on manager's mentorship. We do this to corroborate the results that we obtain from the model. This part of the survey presented respondents with 10 jobs. Each job had manager's name, wages and flexible hours. With each job we provided a slider scale ranging from zero to five and asked respondents to report their expected rating for each manager in each of the jobs. On this data, we project a linear model of reported expected ratings on the gender of the manager, annual wages and flexible hours, in alignment with the parametrization of beliefs in the model of job choice. We use this data as a check on the estimates of the belief parameters obtained from our model which exploits the variation in compensating differentials between the complete and the incomplete scenarios. The objective is to check whether the result on statistical discrimination against female managers that we found from the estimation of the model holds in the direct belief elicitation as well.

Table 20 reports the estimates by all individuals and also by the gender of the respondent. We see that this data not only matches the qualitative conclusion from the belief parameter estimates of statistical discrimination on female managers, but also the average estimates are quite close. Note that this data by itself can only help us estimate α^x and not $\beta^r\alpha^x$ for all $x \in \{G, H, W\}$. However the primary objective of this data is served by corroborating that the sign of α^G is positive in both the estimates obtained from the job choice model using choice and compensating differential data as well as from the directly elicited belief data. This is an important result because it gives us the confidence in the estimates which tell us that individuals do believe females have lower average mentorship quality. The concern of individuals manipulating their responses and misreporting their preferences for female managers is not an issue given this corroborating evidence.[33]

The objective is not to see how close the two estimates of α^G are, because of two additional reasons. First, they are obtained form two unrelated sources of the survey. Second, the estimates of α from the model as explained before could be noisy for individuals whose β^R is close to zero. This is added reason for why we emphasize on using $\beta^R\alpha^G$ as our measure of valuation of statistical discrimination instead of only α^G.

8.2 Further Robustness Checks

A concern is whether individuals followed the instructions provided to them in the beginning of the survey. Identification is a result of individuals assuming that the jobs are identical in any other characteristic which is not observable to them. To ensure this and discipline our estimates, we designed specific questions at the end of the survey both direct and indirect, to infer on whether individuals actually followed the instructions. We dropped 2.2% of the sample as a result of this restriction and re-estimated the model. The estimates were robust to this restriction.

We also dropped 1% of the sample who finished the survey in less than 15 minutes, to deal with survey inattention (Mas & Pallais 2017). The choice of 15 minutes is is driven by the distribution of time completion of the survey - the 1st percentile of completion duration was at 13.1 minutes. Estimates are robust to this restriction as well.

9 Additional Discussions and Implications

Given our results in the incomplete scenarios, it is important to note that observing indifference between male and female managers in the data should not necessarily be interpreted as evidence of no preference of one gender over the other. This can happen

[33] It is necessary to discuss interpretations had the result from the direct belief elicitation appeared opposite or showed no effect of the manager's gender. Such a situation cannot completely be considered as evidence that respondents had manipulated their responses. This is because one cannot tell apart this explanation with an equally plausible explanation of learning from the complete scenarios.

when preferences and beliefs operate in opposite directions as they do in our incomplete scenarios. We cannot comment on whether such beliefs held by individuals are biased or not. In order to do so one would need data on the population distributions of mentorship by gender of manager. In general, there is consistent evidence that individuals do not have a good sense of population distributions (e.g. Wiswall & Zafar (2015), Bordalo, Coffman, Gennaioli & Shleifer (2016), Alesina, Miano & Stantcheva (2019), Bursztyn et al. (2018), Alesina & Stantcheva (2020), Hvidberg, Kreiner & Stantcheva (2020), Bleemer & Zafar (2018)).

There are two primary implications of our research. First, without considering supply side selection, we are missing out on the complete picture of group level inequalities. Additionally studying beliefs and preferences on the supply side is essential because it affects search and equilibrium matches. The second is how firms might respond differently to such beliefs and preferences of workers, which could generate different rates of promotion of females to managerial position. This provides multiple potential avenues for future research extending from this paper. If firms have strong priors that matching workers with their preferred managers increases match productivity, this could potentially lead to females being promoted at higher rates, conditional on productivity. However females could still be promoted at lower rates if firms have high enough discriminatory preferences against females and are willing to forgo increased profits resulting from more efficient matches. Thus in a way worker preferences could be used in testing for discriminatory practices by the firm executives who decide whom to promote to managerial positions. It will be in situations where workers prefer to work for female managers and conditional on productivity females are still promoted at lower rates than males. It will be also interesting to explore whether individual preferences and perceptions about average preferences differ and more importantly whether perceptions are incorrect. In the spirit of Bursztyn, González & Yanagizawa-Drott (2018) this could serve as an additional reason for why female managers are promoted at lower rates.[34] Another avenue for future research is to explore whether having more female managers allows firms to compete profitably for workers with otherwise similar firms, if there is overall preference to work for female managers. Additionally if there exists asymmetric information between incumbent and competing firms (Pinkston (2009), Kahn (2013)) then there are even higher information rents to be taken advantage of.

There are many other instances in which our research applies. Examples include job-

[34]Bursztyn, González & Yanagizawa-Drott (2018) show that in Saudi Arabia, husbands individually prefer having their wives participate in the labor force but misperceive the social norms and believe that such preferences are uncommon on average. Upon correcting their misperceptions, husbands enroll their wives in a costly training program thus increasing female labor force participation.

seekers who have alumni networks in firms and can get some information on manager and manager quality thus affecting their search and consequently the final match. Another example is of individuals who are already employed but seeking to switch teams within firms.

10 Summary

In this paper we provide novel documentation of discrimination by workers on manager's gender in choosing jobs. To answer this question, we design and conduct a hypothetical job choice survey involving a novel information experiment among job seeking students at a highly selective university in India. We present respondents with a series of hypothetical job scenarios consisting of jobs with exogenously varying attributes (annual wages, flexible hours, manager's name and mentorship rating of manager). Respondents are asked to choose their most preferred job and report wage compensating differentials that make them indifferent between jobs. In the first ten scenarios (incomplete scenarios) individuals were shown jobs with all attributes except the mentorship rating of the manager. In the last ten scenarios (complete scenarios) individuals observed all the above attributes in each job. We identify preferences using the variation in compensating differentials within the complete scenarios. The variation in compensating differentials between the complete and incomplete scenarios provides us with the necessary variation to identify beliefs on mentorship. We find that in the absence of information on manager mentorship—chocies driven by both preferences and beliefs— workers are indifferent between male and female managers. However, in the presence of information on manager mentorship, we find a strong preference to work for female managers. Using a structural model of job choice, we estimate that individuals are willing to give up on average 1.7% of average annual wages to work for female managers. Hence in the absence of additional information on manager mentorship, female managers are believed to be worse mentors than male managers. We quantify these negative beliefs against female managers at around 1.6% of average annual wages. We find both gender of workers on average, prefer to work for female managers. However we document rich heterogeneity in the underlying distributions of preferences and beliefs of individuals. Estimating the model for each worker, we find that their preferences and beliefs correlate with demographics in the directions we would expect them. In particular we do not find evidence of negative beliefs on female manager mentorship among female respondents majoring in Science and among those whose mothers are more educated than their fathers. We corroborate these results—on negative beliefs on female manager mentorship—using additional data on directly elicited beliefs. As discussed in details in the previous section, our results suggest that discrimination by firm executives in generating glass ceilings for females at the managerial levels could be under-biased, if conditional on quality females are still promoted at lower rates. To that extent, our paper sheds light on how preferences of workers over their manager characteristics could be used as indirect tests of discrimination by firm executives who decide on promotion, with such additional data on the preferences and beliefs of workers.

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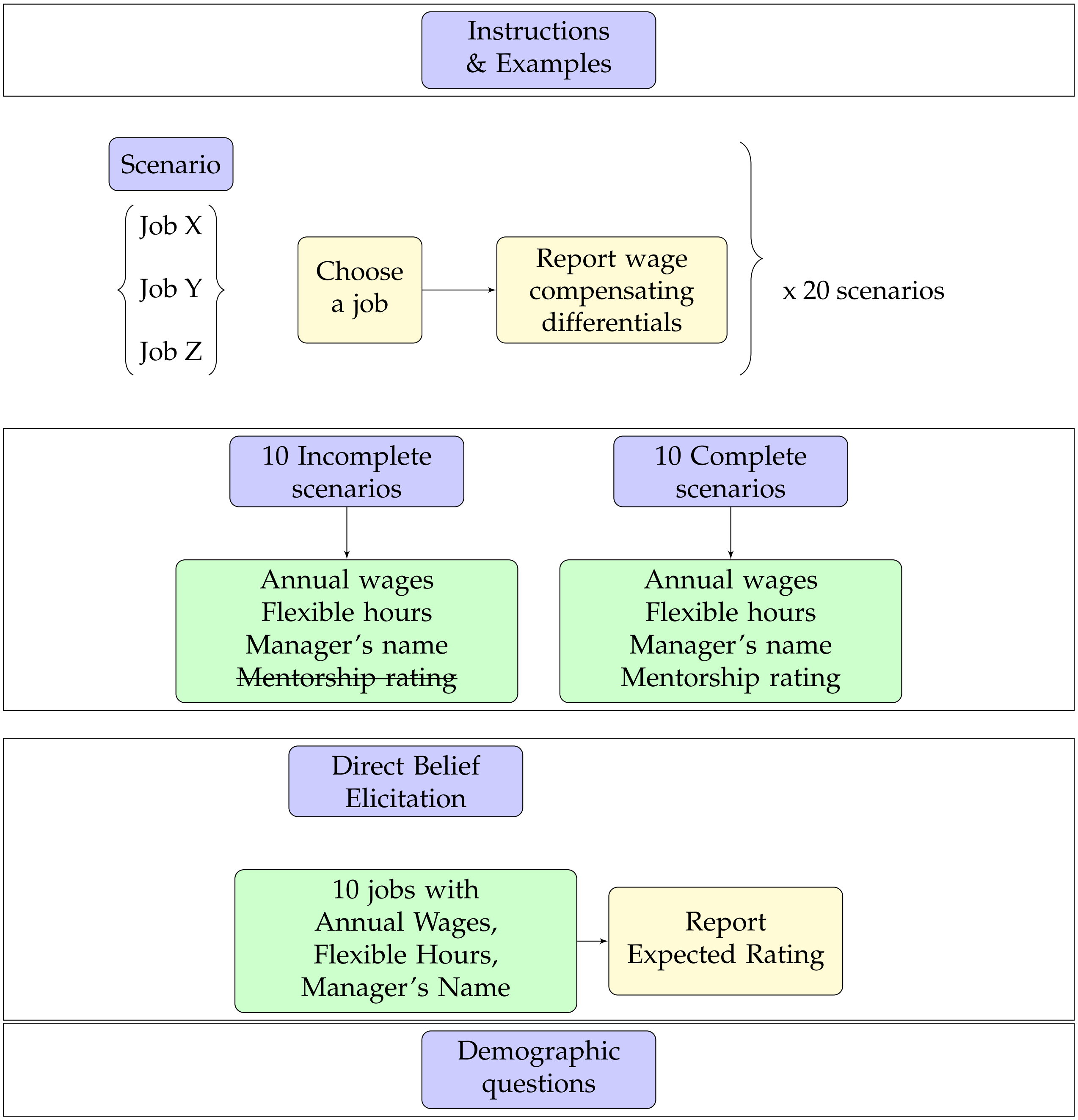
Tables and Figures

Figure 1: Schematic representation of survey flow



Notes: Every scenario consists of three different jobs X,Y and Z. Individuals choose their most preferred job. For the jobs that they did not choose, individuals are asked to report the minimum increase in wages they would need in those jobs for them to choose them instead. There were 20 such scenarios. In the first 10 scenarios, individuals did not observe the mentorship rating of the manager however in the last 10 they did, along with the other attributes.

Figure 2: Definitions of attributes

INSTRUCTIONS

In each question you will see a choice scenario.

A scenario will have 3 jobs (X, Y and Z), which you have to assume have been offered to you.

Each job will have 4 characteristics:

Manager: First name of the team's manager.

Annual wages: Gross annual salary (in lakhs).

Flexible hours: Whether the job allows for flexible hours or not.

Manager rating: This is the average rating of the mentorship of the manger, provided by this manager's current employees in an anonymous survey.

This is a measure of how good of a mentor is this manager to its subordinates.

This rating is on a scale of 1-5. The scale points mean as follows: 1: Poor; 2: Fair 3: Good, 4: Very good and 5: Excellent.

There will be 20 such choice scenarios.

Figure 3: Instructions

INSTRUCTIONS

In each scenario we will first ask you:

A. To choose one job among 3 job options.

Your instructions are:

To assume that all other characteristics, which are NOT MENTIONED here, are THE SAME in all the jobs. For example work from home under each manager is not shown here. You are to assume that its either available or not available in all three jobs. No job is different in anything that you do not observe,

In each scenario, we will then ask you for:

*B. If you were to negotiate wages, how much **minimum increase in wages** you would need in each of the other two jobs, for you choose them instead.*

Your instructions are:

State your wage increase, assuming that it does not change anything else about the job.

Let us give you an example from a survey of food preference.

A. Here you will see me choose one dish among 3 different dishes.

B. Then you will see me state how much MINIMUM drop in prices in the other two dishes would make me choose each of them instead.

Table 1: Complete and Incomplete Scenario Examples

Incomplete Scenario example

Rating of each manager could be different, but the data is unavailable. Anything else that you don't see here, is the SAME across all jobs. Please select your most preferred job.

Attributes	JOB X	JOB Y	JOB Z
Annual Wages	6	6.6	6.4
Flexible hours	yes	no	yes
Manager	Anirban	Shrinita	Arup
Manager rating	N/A	N/A	N/A

Job X

Job Y

Job Z

Complete Scenario example

Anything else that you don't see here, is the SAME across all jobs. Manager rating is on a scale of 1-5. 1:Poor; 2:Fair; 3:Good; 4:Very good; 5:Excellent. Please select your most preferred job.

Attributes	JOB X	JOB Y	JOB Z
Annual Wages	8.2	8	8.6
Flexible hours	yes	no	yes
Manager	Mohan	Mohit	Mahima
Manager rating	3.70	4.00	3.15

Job X

Job Y

Job Z

Notes: Incomplete Scenario Example: Job X and Z have male managers. Job Y has a female manager
Complete Scenario Example: Job X and Y have male managers and Job Z has female manager.
Overall across 10 incomplete scenarios, five scenarios had two jobs with male managers and one job with a female managers and the remaining five had the opposite. Same was the distribution of manager gender in jobs under the 10 complete scenarios. Thus across all jobs half of them had male managers and half and female managers.

Table 2: Complete and Incomplete Scenario Examples
Adapted example for representative US jobs

Incomplete Scenario example

Rating of each manager could be different, but the data is unavailable. Anything else that you don't see here, is the SAME across all jobs. Please select your most preferred job.

Attributes	**JOB X**	**JOB Y**	**JOB Z**
Annual Wages	35k	39k	37k
Flexible hours	yes	no	yes
Manager	John	Susan	Robert
Manager rating	N/A	N/A	N/A

Job X

Job Y

Job Z

Complete Scenario example

Anything else that you don't see here, is the SAME across all jobs. Manager rating is on a scale of 1-5. 1:Poor; 2:Fair; 3:Good; 4:Very good; 5:Excellent. Please select your most preferred job.

Attributes	**JOB X**	**JOB Y**	**JOB Z**
Annual Wages	40k	42k	45k
Flexible hours	yes	no	yes
Manager	James	Barbara	Mary
Manager rating	3.70	4.00	3.15

Job X

Job Y

Job Z

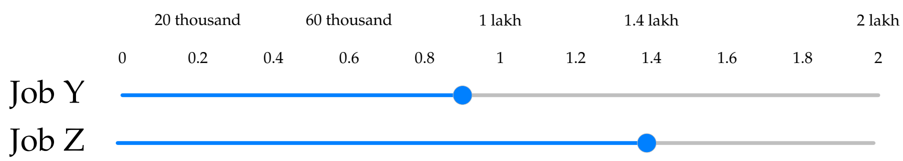
Notes: Incomplete Scenario Example: Job X and Z have male managers. Job Y has a female manager
Complete Scenario Example: Job X and Y have male managers and Job Z has female manager.
Overall across 10 incomplete scenarios, five scenarios had two jobs with male managers and one job with a female managers and the remaining five had the opposite. Same was the distribution of manager gender in jobs under the 10 complete scenarios. Thus across all jobs half of them had male managers and half and female managers.

You chose Job X.

If you were to negotiate your wage, how much MINIMUM INCREASE IN WAGES would you need, in each of the other jobs for you to choose it instead of Job Z?

The scale here ranges from 0 to 2 lakhs.

Attributes	**JOB X**	**JOB Y**	**JOB Z**
Annual Wages	8.2	8	8.6
Flexible hours	yes	no	yes
Manager	Mohan	Mohit	Mahima
Manager rating	3.70	4.00	3.15



Adapted example for representative US jobs

You chose Job X.

If you were to negotiate your wage, how much MINIMUM INCREASE IN WAGES would you need, in each of the other jobs for you to choose it instead of Job Z?

The scale here ranges from 0 to 2 lakhs.

Attributes	**JOB X**	**JOB Y**	**JOB Z**
Annual Wages	40k	42k	45k
Flexible hours	yes	no	yes
Manager	James	Barbara	Mary
Manager rating	3.70	4.00	3.15

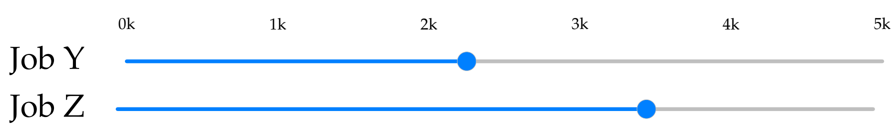


Table 3: Incomplete Scenario Example

Job Choice

Rating of each manager could be different, but the data is unavailable. Anything else that you don't see here, is the SAME across all jobs. Please select your most preferred job.

Attributes	JOB X	JOB Y	JOB Z
Annual Wages	6	6.6	6.4
Flexible hours	yes	no	yes
Manager	Anirban	Shrinita	Arup
Manager rating	N/A	N/A	N/A

Job X

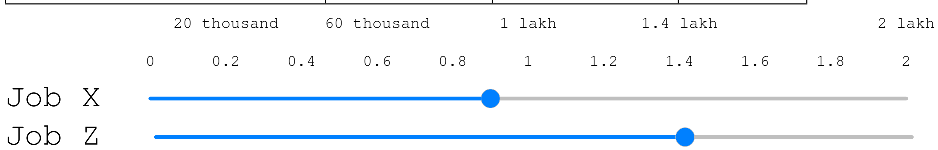
Job Y

Job Z

Compensating differential (*if job chosen was Y*)

You chose Job Y.
If you were to negotiate your wage, how much MINIMUM INCREASE IN WAGES would you need, in each of the other jobs for you to choose it instead of Job Y?
The scale here ranges from 0 to 2 lakhs.

Attributes	JOB X	JOB Y	JOB Z
Annual Wages	6	6.6	6.4
Flexible hours	yes	no	yes
Manager	Anirban	Shrinita	Arup
Manager rating	N/A	N/A	N/A



Notes: Job X and Z have male managers and Job Y has female manager. Across 10 incomplete scenarios, five scenarios had two jobs with male managers and one job with a female managers and the remaining five had two jobs with female managers and one job with a male managers.

Table 4: Complete Scenario Example

Job Choice

Anything else that you don't see here, is the SAME across all jobs. Manager rating is on a scale of 1-5. 1:Poor; 2:Fair; 3:Good; 4:Very good; 5:Excellent. Please select your most preferred job.

Attributes	JOB X	JOB Y	JOB Z
Annual Wages	8.2	8	8.6
Flexible hours	yes	no	yes
Manager	Mohan	Mohit	Mahima
Manager rating	3.70	4.00	3.15

Job X

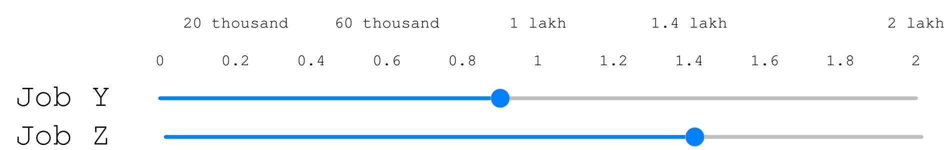
Job Y

Job Z

Compensating differential example (*if job chosen was X*)

You chose Job X.
If you were to negotiate your wage, how much MINIMUM INCREASE IN WAGES would you need, in each of the other jobs for you to choose it instead of Job X?
The scale here ranges from 0 to 2 lakhs.

Attributes	JOB X	JOB Y	JOB Z
Annual Wages	8.2	8	8.6
Flexible hours	yes	no	yes
Manager	Mohan	Mohit	Mahima
Manager rating	3.70	4.00	3.15



Notes: Job X and Y have male managers and Job Z has female manager. Overall across 10 complete scenarios, five scenarios had two jobs with male managers and one job with a female managers and the remaining five had two jobs with female managers and one job with a male managers.

Table 5: Incomplete Scenario Adapted Example for representative US jobs

Job Choice

Rating of each manager could be different, but the data is unavailable. Anything else that you don't see here, is the SAME across all jobs. Please select your most preferred job.

Attributes	JOB X	JOB Y	JOB Z
Annual Wages	35k	39k	37k
Flexible hours	yes	no	yes
Manager	John	Susan	Robert
Manager rating	N/A	N/A	N/A

Job X

Job Y

Job Z

Compensating differential (*if job chosen was Y*)

You chose Job Y.
If you were to negotiate your wage, how much MINIMUM INCREASE IN WAGES would you need, in each of the other jobs for you to choose it instead of Job Y?
The scale here ranges from 0 to 5,000 USD.

Attributes	JOB X	JOB Y	JOB Z
Annual Wages	35k	39k	37k
Flexible hours	yes	no	yes
Manager	John	Susan	Robert
Manager rating	N/A	N/A	N/A

0k 1k 2k 3k 4k 5k

Job X

Job Z

Notes: Job X and Z have male managers and Job Y has female manager. Across 10 incomplete scenarios, five scenarios had two jobs with male managers and one job with a female managers and the remaining five had two jobs with female managers and one job with a male managers.

Table 6: Complete Scenario Adapted Example for representative US jobs

Job Choice

Anything else that you don't see here, is the SAME across all jobs. Manager rating is on a scale of 1-5. 1:Poor; 2:Fair; 3:Good; 4:Very good; 5:Excellent. Please select your most preferred job.

Attributes	**JOB X**	**JOB Y**	**JOB Z**
Annual Wages	40k	42k	45k
Flexible hours	yes	no	yes
Manager	James	Barbara	Mary
Manager rating	3.70	4.00	3.15

Job X

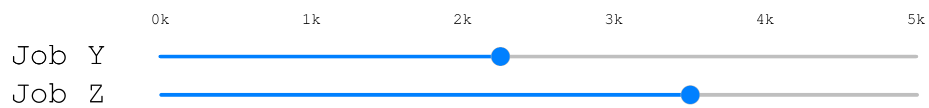
Job Y

Job Z

Compensating differential (*if job chosen was X*)

You chose Job X.
If you were to negotiate your wage, how much MINIMUM INCREASE IN WAGES would you need, in each of the other jobs for you to choose it instead of Job X?
The scale here ranges from 0 to 5,000 USD.

Attributes	**JOB X**	**JOB Y**	**JOB Z**
Annual Wages	40k	42k	45k
Flexible hours	yes	no	yes
Manager	James	Barbara	Mary
Manager rating	3.70	4.00	3.15

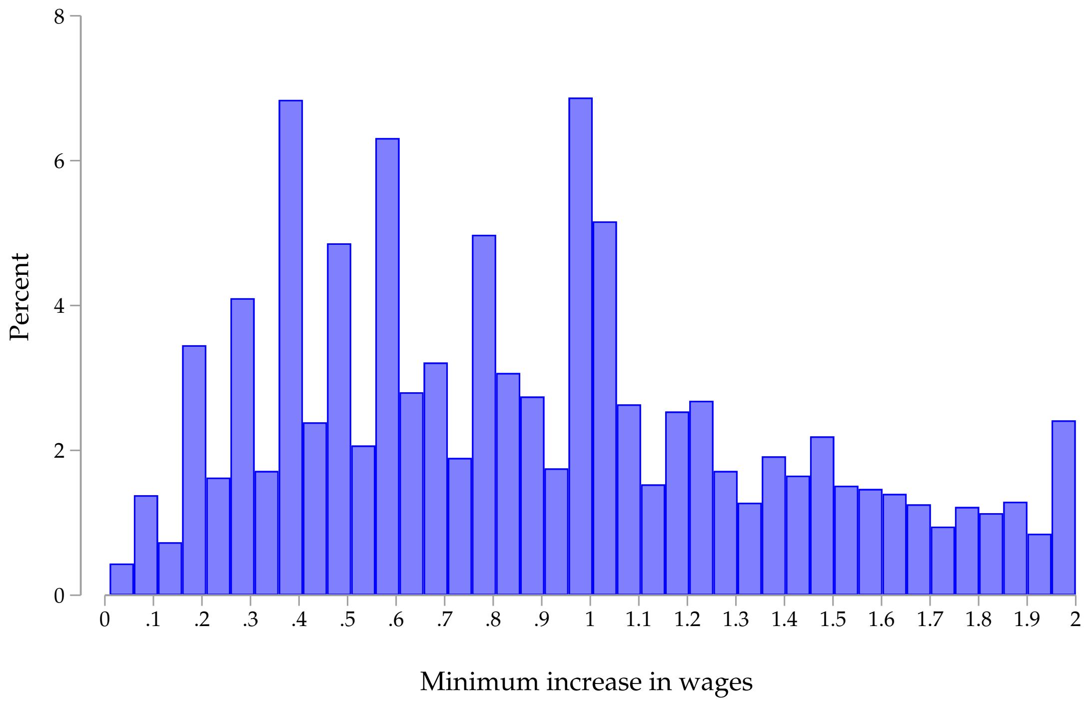


Notes: Job X and Y have male managers and Job Z has female manager. Overall across 10 complete scenarios, five scenarios had two jobs with male managers and one job with a female managers and the remaining five had two jobs with female managers and one job with a male managers.

Table 7: Summary statistics of Job attributes

Variable	**Mean**	**Std. Dev.**	**N**
Female Manager	0.50	0.504	60
Flexible hours	0.53	0.503	60
Annual wages	7.11	1.476	60
Rating	3.41	0.495	30

Figure 4: Reported compensating differentials in unchosen jobs



Notes: The increase in wages are in the units of 1 lakh (hundred thousand) INR. The figure is plotted for values only in between 0 and 2 lakhs.

Table 8: Job Attributes Across Male and Female Managers

Attribute	Male manager	Female Manager	Difference	Std. Diff
Rating	3.373	3.447	0.073	0.103
	(0.519)	(0.485)	(0.183)	
Flexible hours	0.567	0.500	-0.067	-0.093
	(0.504)	(0.509)	(0.131)	
Annual wages	7.080	7.140	0.060	0.029
	(1.529)	(1.445)	(0.384)	

Table 9: Sample Demographics

	Gender		
	Male	Female	Total
580 respondents	58.3	41.7	100
Area of Study:			
Arts	25.1	71.9	44.7
Engineering	49.4	10.7	33.3
Science	25.4	17.4	22.1
Family Income:			
Less than 2 lakhs (Less than $ 9,492)	37.6	24.4	32.1
2 lakhs to 5 lakhs ($9,492 to $23,730)	26.9	24.0	25.7
5 lakhs to 10 lakhs ($23,730 to $47,460)	21.3	30.2	25.0
10 to 20 lakhs ($47,460 to $ 94,921)	11.5	15.3	13.1
Above 20 lakhs (Above $ 94,921)	2.7	6.2	4.1
Mother's Education:			
Below High School	17.8	11.2	15.0
High School	32.8	18.6	26.9
Bachelor's	38.5	46.3	41.7
Master's	8.0	16.9	11.7
Above Master's	3.0	7.0	4.7
Father's Education:			
Below High School	9.2	7.4	8.4
High School	21.3	11.2	17.1
Bachelor's	51.5	55.4	53.1
Master's	13.9	17.8	15.5
Above Master's	4.1	8.3	5.9
Mother's Occupation:			
Government	10.9	15.3	12.8
Home-Maker	70.1	63.2	67.2
Not Applicable	4.4	3.3	4.0
Private Sector	4.7	8.7	6.4
Self-employed	9.8	9.5	9.7
Father's Occupation:			
Government	30.8	33.1	31.7
Home-Maker	3.3	0.8	2.2
Not Applicable	16.3	11.2	14.1
Private Sector	16.9	20.7	18.4
Self-employed	32.8	34.3	33.4

Notes: All variables are categorical. Numbers represent percentages. The parental occupation category of 'Not Applicable' refers to deceased parent. Variables on income categories are in INR and have their corresponding purchasing power parity adjusted equivalent USD below each category

Table 10: Percent of chosen jobs with male and female managers, by scenarios

Respondent	*All*		*Female*		*Male*	
Scenario \ *Manager*	Male	Female	Male	Female	Male	Female
Incomplete	48.2	51.8	48.1	52.9	48.3	51.7
Complete	38.9	61.1	38.8	61.2	38.9	61.1

Table 11: Average compensating differentials in unchosen jobs, by gender of manager across scenarios

	Male manager	Female Manager	Difference	St Diff
Incomplete scenarios	0.957	1.020	-0.063***	-0.046
	(0.965)	(0.998)	(0.018)	
Complete scenarios	1.100	1.038	0.061***	0.042
	(1.058)	(0.977)	(0.019)	

Notes: Units are in 1 lakh (hundred thousand) INR

Table 12: Difference-in-Differences Estimates from the Complete Scenarios Data

VARIABLES	Margins
Female Worker	-0.001
	(0.010)
Female manager	0.081***
	(0.009)
Female Worker X Female Manager	0.001
	(0.014)
Annual wages	0.347***
	(0.019)
Mentorship Rating	0.484***
	(0.009)
Flexible hours	0.262***
	(0.009)
Scenarios FE	yes
Observations	17,400

Notes: The estimates show the marginal effects of each of the attributes in a difference and difference specification. Standard errors bootstrapped at the individual level with 1000 replications. The total number of observations is 17,400 because it uses individual level choice data on 3 jobs in each of the 10 complete scenarios for 580 individuals.

Table 13: Complete & Incomplete Scenarios: Jointly Estimated

Incomplete Scenarios			Complete Scenarios		
Parameters	in 10^5 INR	% of wages	*Parameters*	in 10^5 INR	% of wages
$\tilde{\beta}^G = \beta^G + \beta^R \alpha^G$	-0.007	-0.01%	β^G (Male Manager)	-0.118***	-1.7%
	(0.012)			(0.019)	
$\tilde{\beta}^H = \beta^H + \beta^R \alpha^H$	1.136***	16.1%	β^H (Flexible Hours)	0.776***	11.1%
	(0.068)			(0.027)	
$\tilde{\beta}^W = \beta^W + \beta^R \alpha^W$	1.132***	16%	β^W (Annual wages)	1	
	(0.059)				
			β^R (Mentorship)	0.793***	11.3%
				(0.029)	
Observations	11,600			11,600	

Notes: The table shows estimates from estimating the system of equations (14). Estimates are represented in two sets of units - the first is in hundred thousand INR and the second converts those units as a percent of average annual wages. Standard errors are computed using the the block bootstrapap at the individual level with 1000 replications. β^W is normalized to 1. ***, **, * denote statistical significance at 1, 5, and 10%, respectively.

Table 14: Estimates of Belief Parameters

Belief Parameter	
α^G (Male managers)	0.140***
	(0.024)

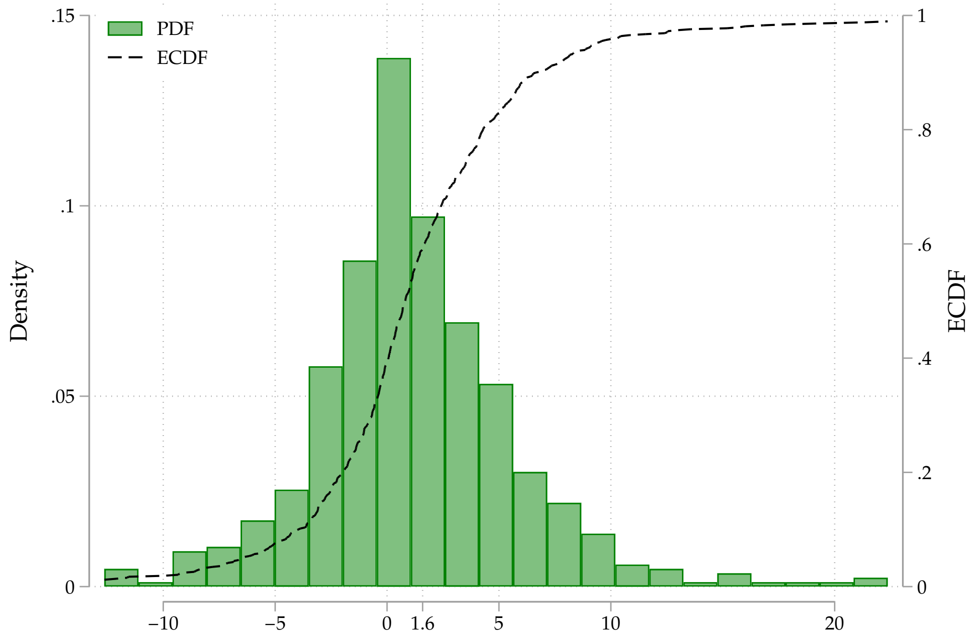
Notes: Standard errors are computed using the block bootstrapap at the individual level with 1000 repetitions. Parameters are estimated by jointly estimating the complete and incomplete scenarios and using estimates of β^R $\tilde{\beta}^G$ and β^G presented in Table 13. The estimates come from the equation $\alpha^G = \frac{\tilde{\beta}^G - \beta^G}{\beta^R}$. ***, **, * denote statistical significance at 1, 5, and 10%, respectively.

Table 15: Estimates of Valuation of Beliefs

Belief Parameter	in 10^5 INR	% of wages
$\beta^R \alpha^G$ (Male managers)	0.112***	1.6%
	(0.024)	

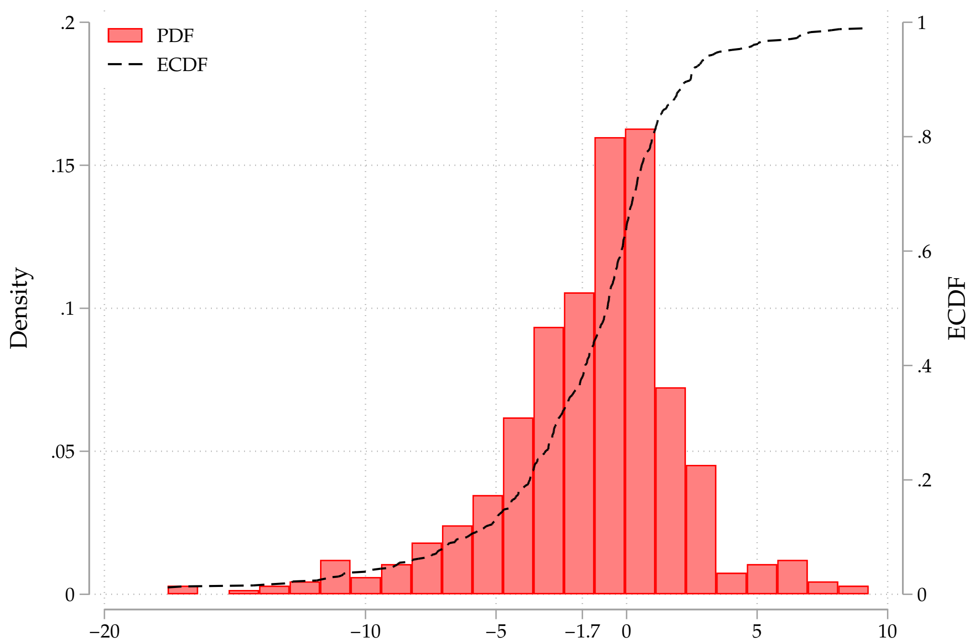
Notes: Note that the estimates come from the equation $\beta^R \alpha^G = \tilde{\beta}^G - \beta^G$ for all $x \in \{G, W, H\}$ presented in Table 13. The standard errors are the block bootstrapapped at the individual level with 1000 repetitions. Parameters are estimated by jointly estimating the complete and incomplete scenarions. ***, **, * denote statistical significance at 1, 5, and 10%, respectively. Average annual wages equal 7 lakh INR ($\approx$ \$38.8 thousand in PPP)

Figure 5: Distribution of Individual Beliefs



Notes: The figure plots the histogram and the smoothed empirical cumulative distribution function of individual beliefs obtained by estimating the model for each individual. The units on the x-axis are in percent of average of annual wages.

Figure 6: Distribution of Individual Preferences



Notes: The figure plots the histogram and the smoothed empirical cumulative distribution function of individual preferences obtained by estimating the model for each individual. The units on the x-axis are in percent of average of annual wages.

Table 16: Jointly Estimated Complete & Incomplete Scenarios: By Gender of the Respondent

Incomplete Scenarios			**Complete Scenarios**		
Parameters	Female	Male	*Parameters*	Female	Male
$\tilde{\beta}^G = \beta^G + \beta^R\alpha^G$	-0.017	-0.000	β^G (Male Manager)	-0.096***	-0.135***
	(0.016)	(0.018)		(0.018)	(0.019)
$\tilde{\beta}^H = \beta^H + \beta^R\alpha^H$	1.047***	1.193***	β^H (Flexible Hours)	0.739***	0.803***
	(0.038)	(0.039)		(0.020)	(0.021)
$\tilde{\beta}^W = \beta^W + \beta^R\alpha^W$	1.350***	1.382***	β^W (Annual wages)	1	1
	(0.055)	(0.061)			
			β^R (Mentorship)	0.732***	0.835***
				(0.024)	(0.025)
Observations	4,840	6,760		4,840	6,760

Notes: Standard errors are computed using the block bootstrapap with 1000 replications. β^W is normalized to 1. Units are in hundred thousand INR. ***, **, * denote statistical significance at 1, 5, and 10%, respectively.

Table 17: Jointly Estimated Complete & Incomplete Scenarios: By Departments

	Arts		Science		Engineering	
Parameters	Preferences	Beliefs	Preferences	Beliefs	Preferences	Beliefs
$\tilde{\beta}^G$	-0.006		-0.015		-0.004	
	(0.021)		(0.020)		(0.019)	
β^G	-0.128***		-0.0987***		-0.119***	
	(0.0345)		(0.0268)		(0.0269)	
β^R	0.795***		0.785***		0.793***	
	(0.0430)		(0.0594)		(0.0566)	
$\beta^R\alpha^G$		0.122***		0.0841***		0.115***
		(0.0441)		(0.0309)		(0.0345)
Observations	10,360	10,360	5,120	5,120	7,720	7,720

Notes: The table reports estimates of preference and belief parameters by running the model for each field of study (Arts, Science and Engineering). The table only shows coefficients of interest. β^G is the preference parameter for male managers. Note that $\beta^R\alpha^G = \tilde{\beta}^G - \beta^G$ is the valuation of beliefs of male manager mentorship. It does not report the coefficients from the incomplete scenarios and that of flexible hours. As before, the preference parameter on wages is normalized to 1. The estimates are in units of hundred thousand INR.

Table 18: Jointly Estimated Complete & Incomplete Scenarios: By Departments and Gender of respondent

Panel A: Female Respondents

	Arts		Science		Engineering	
Parameters	Preferences	Beliefs	Preferences	Beliefs	Preferences	Beliefs
$\tilde{\beta}^G$	-0.016		-0.031		0.002	
	(0.019)		(0.028)		(0.030)	
β^G	-0.0977***		-0.0817**		-0.107***	
	(0.0232)		(0.0368)		(0.0411)	
β^R	0.784***		0.653***		0.510**	
	(0.0469)		(0.0789)		(0.222)	
$\beta^R\alpha^G$		0.0816***		0.0507		0.109**
		(0.0300)		(0.0471)		(0.0547)
Observations	6,960	6,960	1,680	1,680	1,040	1,040

Panel A: Male Respondents

	Arts		Science		Engineering	
Parameters	Preferences	Beliefs	Preferences	Beliefs	Preferences	Beliefs
$\tilde{\beta}^G$	0.014		-0.007		-0.005	
	(0.050)		(0.027)		(0.022)	
β^G	-0.190**		-0.107***		-0.121***	
	(0.0952)		(0.0352)		(0.0296)	
β^R	0.819***		0.850***		0.836***	
	(0.0930)		(0.0709)		(0.0544)	
$\beta^R\alpha^G$		0.204*		0.100**		0.116***
		(0.119)		(0.0407)		(0.0370)
Observations	3,400	3,400	3,440	3,440	6,680	6,680

Notes: The table reports estimates of preference and belief parameters by running the model for each possible pair of field of study (Arts, Science and Engineering) and gender of the respondent (male and female). β^G is the preference parameter for male managers. Note that $\beta^R\alpha^G = \tilde{\beta}^G - \beta^G$ is the valuation of beliefs of male manager mentorship. The table only shows coefficients of interest. It does not report the coefficients from the incomplete scenarios and that of flexible hours. As before, the preference parameter on wages is normalized to 1. The estimates are in units of hundred thousand INR.

Table 19: Jointly Estimated Complete & Incomplete Scenarios: By Relative Parental Education

	Father more educated		Mother more educated	
Parameters	Preferences	Beliefs	Preferences	Beliefs
$\tilde{\beta}^G$	-0.005		-0.020	
	(0.013)		(0.033)	
β^G	-0.115***		-0.145***	
	(0.020)		(0.055)	
β^R	0.814***		0.644***	
	(0.032)		(0.096)	
$\beta^R\alpha^G$		0.109***		0.125
		(0.024)		(0.076)
Observations	20,200	20,200	3,000	3,000

Notes: The table reports estimates of preference and belief parameters by running the model- first for the subsample whose mothers are at least as much or more educated than their fathers and the second where the father is more educated than the mother. The table only shows coefficients of interest. β^G is the preference parameter for male managers. Note that $\beta^R\alpha^G = \tilde{\beta}^G - \beta^G$ is the valuation of beliefs of malae manager mentorship. It does not report the coefficients from the incomplete scenarios and that of flexible hours. As before, the preference parameter on wages is normalized to 1. The estimates are in units of hundred thousand of INR.

Figure 7: Expected Rating

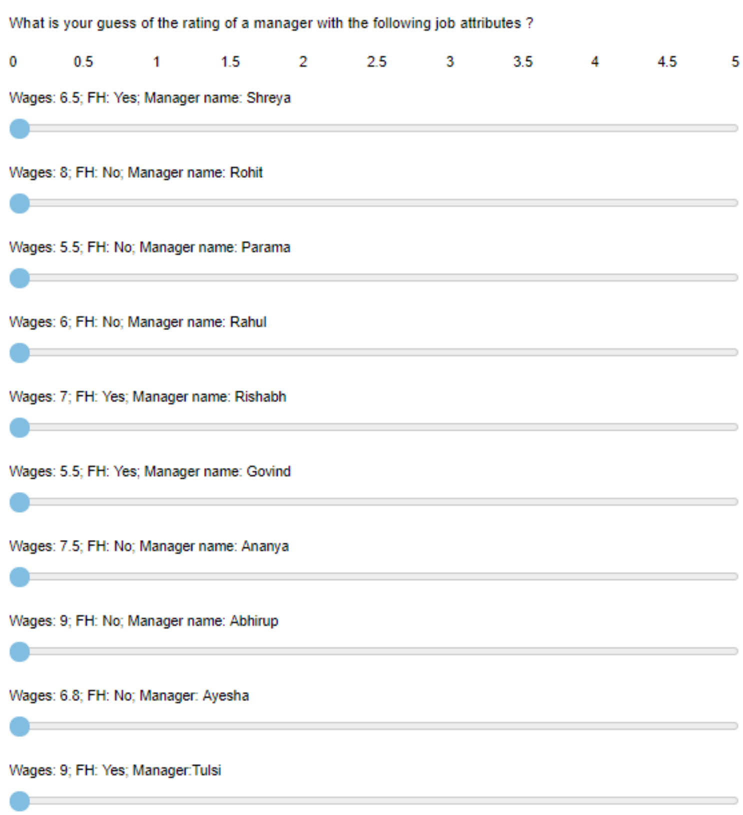


Table 20: Estimates of Expected Beliefs from Directly Elicited Belief data

	Model			Data on beliefs		
Belief Parameters	All	Females	Males	All	Females	Males
α^G (Male managers)	0.140***	0.108***	0.161***	0.091***	0.099***	0.084***
	(0.024)	(0.033)	(0.033)	(0.022)	(0.034)	(0.033)
α^W (Annual wages)	0.465***	0.478***	0.457***	0.428***	0.425***	0.429***
	(0.053)	(0.077)	(0.074)	(0.003)	(0.004)	(0.004)
α^H (Flexible hours)	0.449***	0.422***	0.467***	0.358***	0.352***	0.362***
	(0.040)	(0.060)	(0.056)	(0.021)	(0.032)	(0.030)

Notes: Standard errors bootstrapped at the individual level with 1000 repetitions. These estimates come from projecting a linear model on the data of reported expected manager's rating in each of 10 different jobs with annual wages, flexibility of hours and manager's name. The linear projection takes the form of $R_{ij} = \alpha^G G_j + \alpha^W W_j + \alpha^H H_j + \eta_{ij}$.

A Appendix

A.1 Details of Administration and Collection of Data

The online survey was designed and implemented on Qualtrics. Recruitment of students was done by the research assistants, who had previous experience in recruiting students for surveys and RCTs. In the midst of a nationwide lock-down, we administered the online survey in three key steps.

Step 1: The RAs, based on their previous experience, sent a sign-up link to each department's class' student representative, who distributed the link in the class lists. The sign-up sheet apart from containing the consent form, for them to sign, had asked about their email addresses to which the link of the survey would be sent, basic demographics, department, faculty of study (Arts/Science/Engineering) and level (Bachelors or Masters) and year of study. Students were also allowed to choose the date and the time at which they would like to take the survey. They had a choice among 4 dates starting April 8th to April 11th. On their selected date they had a choice of 1 among 6 time slots : 10am, 12 noon, 5pm, 7pm, 9pm and 11pm. We observed that pilots which had specified time-slots along with dates had higher completion rates than those with just dates. The sign-up form ended with a summary. The sign-up form was designed to automatically send them their signed-up form to their email address. This enabled us to automatically have the consent form's signed copy sent to the participant.

Step 2: Upon receiving sign-ups we scheduled emails to be sent out with unique links to the survey for each participant, an hour before each they were scheduled to participate in the survey. Hence that link could not be used on two different devices, to fill up the survey. The survey was also designed to prevent ballot-boxing i.e. once a survey is completed using a link, that link when clicked on again would show a confirmation of the survey being already completed. The links were designed to expire within 24 hours. Thanks to the extensive pilot done before, we did not face any technical difficulties while implementing the survey. Debriefs with pilot participants were extremely helpful in rewording the questions in order to maximize correct communication and understanding.

Step 3: The mode and details of online payment were selected at the last section of the survey. The options included direct bank transfers, PayPal and UPI (Unified Payment Interface). The payment was processed to the list of students who were verified within the pre-stated timeline for each mode of payment.

A.2 Identification

Let individual $i \in \{1, ..., N\}$ have preferences on attributes X_j in job $j \in \{1, ..., J\}$ given by the function

$$U_{ij} = u_i(X_j) + \epsilon_{ij}$$

Identification is achieved in two-steps. We will first show identification of preferences when information is complete in Step 1. Then with incomplete information in Step 2, we will show that we can identify beliefs given preferences.

Step 1: Identifying preferences

Individuals form expectations when they report their job choices and compensating differentials. Hence

$$\mathbb{E}_i[U_{ij}|X_j] = u_i(X_j) + \mathbb{E}_i[\epsilon_{ij}|X_j]$$

A compensating differential of Δ_{ijk} makes i indifferent between jobs j and k when the i observes X_j and X_k. Hence, given that a compensating differential only increases wages and changes nothing else about the job, and normalizing the preference parameter on wages to 1, we have

$$\begin{aligned} \mathbb{E}_i[U_{ik}|X_k, \Delta_{ijk}] &= \Delta_{ijk} + u_i(X_k) + \mathbb{E}_i[\epsilon_{ik}|X_k, \Delta_{ijk}] \\ &= \Delta_{ijk} + u_i(X_k) + \mathbb{E}_i[\epsilon_{ik}|X_k] \end{aligned}$$

Given that everything else about the job is the same, we have $\mathbb{E}_i[\epsilon_{ik}|X_k] = \mathbb{E}_i[\epsilon_{ij}|X_j]$ for all jobs $j \neq k$.

Since by definition $\Delta_{ijk} = \mathbb{E}_i[U_{ij}|X_j] - \mathbb{E}_i[U_{ik}|X_k, \Delta_{ijk}]$ we now have

$$\Delta_{ijk} = u_i(X_j) - u_i(X_k)$$

As number of scenarios goes to infinity, for each individual i this identifies preferences $u_i(.)$ as long as $Var_i(u_i(X_j)|X_j) \neq 0$.

Step 2: Identifying beliefs given preferences

Now when i observes $\widetilde{X_j} \equiv X_j \setminus R_j$ for each job $j \in \{1, ..., J\}$, i forms beliefs on R_j given $\tilde{X}_j$ according to $G_i(R|\tilde{X})$. Now we have

$$\mathbb{E}_i[U_{ij}|\widetilde{X_j}] = \mathbb{E}_i[u_i(X_j)|\widetilde{X_j}] + \mathbb{E}_i[\epsilon_{ij}|\widetilde{X_j}]$$

A compensating differential of $\widetilde{\Delta_{ijk}}$ makes i indifferent between jobs j and k while observing $\widetilde{X_j}$ and $\widetilde{X_k}$ respectively. Hence, given that the compensating differential only increases wages and changes nothing else about the job, and normalizing the preference parameter on wages to 1, we have

$$\begin{aligned}
\mathbb{E}_i[U_{ik}|\widetilde{X_k}, \widetilde{\Delta_{ijk}}] &= \widetilde{\Delta_{ijk}} + \mathbb{E}_i[u_i(X_k)|\widetilde{X_k}] + \mathbb{E}_i[\epsilon_{ik}|\widetilde{X_k}, \widetilde{\Delta_{ijk}}] \\
&= \widetilde{\Delta_{ijk}} + \mathbb{E}_i[u_i(X_k)|\widetilde{X_k}] + \mathbb{E}_i[\epsilon_{ik}|\widetilde{X_k}]
\end{aligned}$$

Given that everything else about the job is the same, we have $\mathbb{E}_i[\epsilon_{ik}|\widetilde{X_k}] = \mathbb{E}_i[\epsilon_{ij}|\widetilde{X_j}]$ for all jobs $j \neq k$.

Since by definition $\widetilde{\Delta_{ijk}} = \mathbb{E}_i[U_{ij}|\widetilde{X_j}] - \mathbb{E}_i[U_{ik}|\widetilde{X_k}, \widetilde{\Delta_{ijk}}]$, we have

$$\begin{aligned}
\widetilde{\Delta_{ijk}} &= \mathbb{E}_i[u_i(X_j)|\widetilde{X_j}] - \mathbb{E}_i[u_i(X_k)|\widetilde{X_k}] \\
&= \int u_i(X_j) dG_i(R|\widetilde{X} = \widetilde{X_j}) - \int u_i(X_k) dG_i(R|\widetilde{X} = \widetilde{X_k})
\end{aligned}$$

Assuming moments exist, as number of scenarios go to infinity, the above identifies individual i's belief distribution $G_i(R|\tilde{X})$, given $\widetilde{\Delta_{ijk}}$ and $u_i(.)$ identified from Step 1. The model is also identified as the number of attributes goes to infinity as long as it approaches infinity at a slower rate than the number of scenarios approach infinity.

Additionally note that beliefs $G_i(R|\tilde{X})$ are not identified under two circumstances. First, if i does not care about R then the chocies made and compensations reported are not driven by in whatever way i may expect R to vary with $\tilde{X}$. To see this mathematically, if i does not care about R then the above set of equations become independent of $G_i(R|\tilde{X})$

because $\mathbb{E}_i[u_i(X_j)|\widetilde{X_j}] = \mathbb{E}_i[u_i(\widetilde{X_j})|\widetilde{X_j}] = u_i(\widetilde{X_j})$. Second if R is independent of $\tilde{X}$, then no variation in $\tilde{X}$ can generate any variation in the beleifs and thus will not be reflected in the choices and compensating differentials. To see this mathematically, if R is independent of $\tilde{X}$, then $G_i(R|\tilde{X}) = G_i(R)$. This makes $\mathbb{E}_i[u_i(X_j)|\widetilde{X_j}] \equiv \mathbb{E}_i[u_i(\widetilde{X_j}, R_j)|\widetilde{X_j}]$ a function which is independent of R_j by the Law of Iterated Expectations.

A.3 Estimation details

We implement the joint estimation of individual indifference in the complete and incomplete scenarios in a fully interacted model by stacking up the matrices of observables across the complete and the incomplete scenarios. In particular we estimate the following constrained least squares regression with no constant,

$$\begin{bmatrix} \mathbf{\Delta_{jk}} \\ \vdots \\ \mathbf{\tilde{\Delta}_{jk}} \\ \vdots \end{bmatrix} = \begin{bmatrix} \mathbf{X_j} - \mathbf{X_k} & \mathbf{0} \\ \vdots & \vdots \\ \mathbf{0} & \mathbf{\tilde{X}_j} - \mathbf{\tilde{X}_k} \\ \vdots & \vdots \end{bmatrix}' (\boldsymbol{\beta} \quad \tilde{\boldsymbol{\beta}}) + \mathbf{e} \tag{16}$$

where the constraint is the normalization for the preference parameter on wages to be equal to one. The standard errors are computed using the block bootstrapap at the student level. This accounts for any arbitrary correlation between responses at the student level.

The the block bootstrapap algorithm is as follows: Sample contains N individuals.

1. Generate B the block bootstrap samples of N individuals each.
   For each $b = 1, .., B$

2. Estimate the model for each member in the bootstrap sample, by bootstrapping each member's responses.

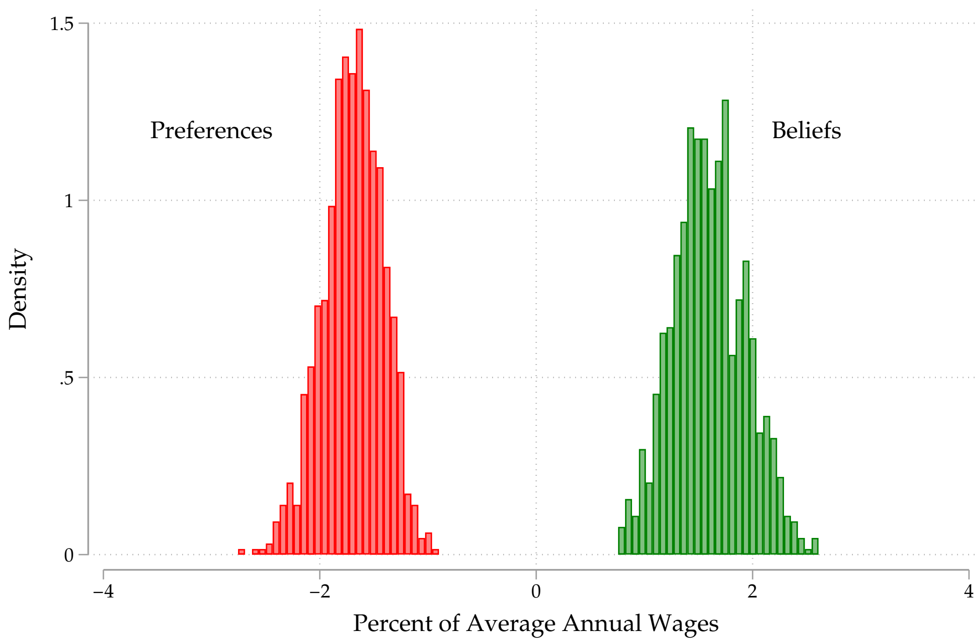
   Obtain $\hat{\beta}_i^{(b)}$ and compute its sample mean $\hat{\beta}^{(b)} = \sum_{i=1}^{N} \hat{\beta}_i^{(b)}$

Compute mean and standard deviation of the B estimates in hand to generate estimates of the bootstrap mean and bootstrap standard error.

$$\hat{\mathbb{E}}(\beta_i) = \frac{1}{B} \sum_{b=1}^{B} \hat{\beta}^{(b)}$$

$$\widehat{\text{std error}}(\beta_i) = SD(\hat{\beta}^{(b)})$$

Figure 8: Bootstrap Distribution of Beliefs and Preferences on Male Mangers

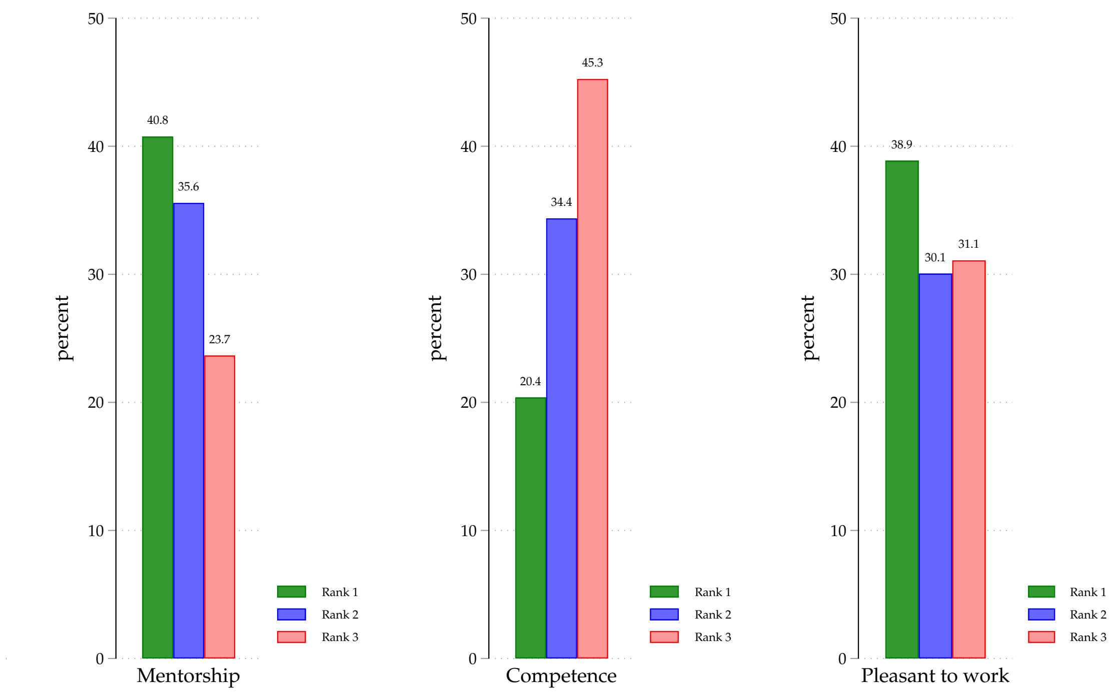


Notes: The figure shows bootstrap discributions of beliefs and preferences in units of percentage of average annual wages. The bootstrap distirbutions are obtained from 1000 block bootsrapped samples, using the alogrithm described in Appendix A.3. These bootstrap distributions are used for estimation of means and standard erros of preferences and beliefs.

A.4 Descriptive evidence on mentorship

After respondents answered choice and compensating differentials questions for twenty scenarios, we asked them descriptive questions on different qualities of a manger along with demographic questions. In particular, we asked to rank three different qualities of managers that they would care about the most- competence, mentorship and peasant to work with. These rankings are plotted in Figure 9 for each of the above qualities. 40.8% of individuals rank mentorship above the other two qualities and more than 75% rank it at either 1 or 2. This shows a stark difference on how on average job-seekers care about mentorship in their managers above other qualities.

Figure 9: Ranking of manager qualities



Notes: This figure plots data on what respondents care about in their managers among the following qualities - mentorship, competence, pleasant to work.

A.5 Generic model

In this section, we delineate a more generic model than the one presented in the main paper. The identifying assumptions remain the same. However, we relax the interpretation of the attribute of mentorship of the manager. In this specification, individuals care about overall manager quality (Q) besides caring about wages, flexible hours and gender of the manager. The mentorship rating acts as a signal of overall manager quality. Individuals care about this overall manager quality. The purpose of this generic model is to show that the results of statistical discrimination still holds.

Redefining the set of attributes to $A \equiv \{G, W, H, Q\}$, the utility of individual i takes the same linear form,

$$U_{ij} = \sum_{x \in A} \beta_i^x x_j + \epsilon_{ij} \tag{17}$$

Observe that now in both the complete and the incomplete scenarios, individuals will need to form expectations on the manager quality. In the incomplete scenario they will not have information on the manager's mentorship rating whereas in the complete scenarios they will have information about it. The expected utilities in the complete and the incomplete scenarios take the following forms-

$$\begin{aligned} \text{Incomplete Scenarios: } \mathbb{E}_i[U_{ij}|\tilde{X}_j] &= \sum_{x \in A \setminus Q} \beta_i^x x_j + \beta_i^Q \mathbb{E}_i(Q_j|\tilde{X}_j) + \mathbb{E}_i(\epsilon_{ij}|\tilde{X}_j) \\ \text{Complete Scnearios: } \mathbb{E}_i[U_{ij}|X_j] &= \sum_{x \in A \setminus Q} \beta_i^x x_j + \beta_i^Q \mathbb{E}_i(Q_j|X_j) + \mathbb{E}_i(\epsilon_{ij}|X_j) \end{aligned} \tag{18}$$

As explained above in both the expected utilities the individuals forms expectations on manager quality. But in the complete scenario the individual has the additional information of manager's mentorship rating. We parameterize the expectation on manager's quality in the following way-

$$\begin{aligned} \text{Complete Scenarios: } \mathbb{E}_i(Q_j|X_j) &= \sum_{x \in A \setminus Q} \gamma_i^x x_j + \gamma_i^R R_j + \mathbb{E}_i(\zeta_i|X_j) \\ \text{Incomplete Scenarios: } \mathbb{E}_i(Q_j|\tilde{X}_j) &= \sum_{x \in A \setminus Q} \gamma_i^x x_j + \gamma_i^R \mathbb{E}[R_j|\tilde{X}_j] + \mathbb{E}_i(\zeta_i|\tilde{X}_j) \\ &= \sum_{x \in A \setminus Q} \tilde{\gamma}_i{}^x x_j + \mathbb{E}_i(\zeta_i|\tilde{X}_j) \end{aligned} \tag{19}$$

Incorporating the above in the expected utility functions in both scenarios, we have

$$\begin{aligned} \text{Complete Scenarios: } \mathbb{E}_i[U_{ij}|X_j] &= \sum_{x \in A \setminus Q} (\beta_i^x + \beta_i^Q \gamma_i^x) x_j + \mathbb{E}_i(\epsilon_{ij}|X_j) \\ \text{Incomplete Scenarios: } \mathbb{E}_i[U_{ij}|\tilde{X}_j] &= \sum_{x \in A \setminus Q} (\beta_i^x + \beta_i^Q \tilde{\gamma}_i^x) x_j + \mathbb{E}_i(\epsilon_{ij}|\tilde{X}_j) \end{aligned} \tag{20}$$

Then with the same set of identifying assumptions, given the reported compensating differentials and normalizing $\beta^W = 1$, we have the following indifference conditions

$$\begin{aligned} \Delta_{ijk} &= \sum_{x \in A \setminus Q} \underbrace{(\beta_i^x + \beta_i^Q \gamma_i^x)}_{\beta_i^{x(CS)}} (x_j - x_k) \\ \tilde{\Delta}_{ijk} &= \sum_{x \in A \setminus Q} \underbrace{(\beta_i^x + \beta_i^Q \tilde{\gamma}_i^x)}_{\beta_i^{x(IS)}} (x_j - x_k) \end{aligned} \tag{21}$$

The differences in the coefficients infront of the gender differences across the complete and the incomplete scenarios give us.

$$\beta_i^{G(CS)} - \beta_i^{G(IS)} = \beta_i^Q (\gamma_i^G - \tilde{\gamma}_i^G) \tag{22}$$

γ encapsulates the information on manager quality given X_j whereas $\tilde{\gamma}$ encapsulates the information on manager quality given $\tilde{X}_j$ i.e. in the absence of the information on manager quality. In presence of statistical discrimination against female managers this should be negative. This is what our estimates show, given that individual care positively about the quality of the manager. Thus under this model specification statistical discrimination is identified. Observe the analogy with the model presented in the main paper. Here too, if the individual does not care about the quality of the manager (i.e. $\beta^Q = 0$), the parameters identified from the complete and the incomplete scenarios must be identical, because the variation in information revelation will have no affect.