WORKER-SIDE DISCRIMINATION: BELIEFS AND PREFERENCES

EVIDENCE FROM AN INFORMATION EXPERIMENT WITH JOBSEEKERS*

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Abstract

Tight labor markets are associated with high costs of worker-turnover. In such settings, firms might put significant weight on whom workers want to work for, while deciding promotions. Should workers prefer not to work for female managers, it could lower the chances of females being promoted. In this paper, we provide novel evidence on the distribution of workers' preferences on manager gender and their beliefs on managers' mentoring ability, which affects their job search and choice. In the absence of information on manager mentoring ability, workers are indifferent to manager gender. However, upon receiving information on manager mentorship ability, workers prefer to work for female managers—as exhibited by their willingness to forgo 1.3–2.2% of average annual wages. Hence, absent additional information on mentorship skill, workers on average believe that female managers' mentoring ability is worse than male managers', with the magnitude of this evaluation corresponding to a wage differential of 1.6% of average annual wages. These averages mask rich heterogeneity. We find that 60% of workers prefer to work for female managers, and in the absence of information on mentorship ability, 62% believe male managers to be better mentors. An ex-post survey directly eliciting worker beliefs corroborates this finding. We find policy-relevant heterogeneity by maternal education level, parental employment status and worker major. Our results imply that the distribution of worker preferences and beliefs could be used as indirect tests for discriminatory practices by firms in tight labor markets. *JEL* codes: J16, J71, J24, D83

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1 Introduction

Managers differ considerably in their ability to manage workers, which directly impacts workers' careers (Frederiksen, Kahn & Lange 2020). Managers with a high ability to manage workers have much lower attrition and turnover among their subordinates (Hoffman & Tadelis (2021), Lazear, Shaw & Stanton (2015))[1]. While workers value many nonpecuniary benefits of their jobs (Dey & Flinn (2005), Blau & Kahn (2017), Mas & Pallais (2017), Wiswall & Zafar (2018), Taber & Vejlin (2020)), it remains an open question as to how manager gender and ability directly influences workers' job choice.

The job choice of workers, especially jobseekers, depends on—in addition to their preferences—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, should workers prefer not to work for women, they would need to be paid a wage premium to work for female managers. In equilibrium, this could lower the rate at which women are hired or promoted to managerial positions and thus generate a glass ceiling. Thus, worker preferences and beliefs are direct objects of interest given the high turnover costs of replacing and training workers, especially in tight labor markets.

In this paper, we provide novel evidence on the distributions of worker preferences on manager gender and 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 forgo wages to work for their preferred managers in an otherwise-identical job.[2] This willingness to trade off wages is driven by their preferences on observable attributes and beliefs on unobservable attributes that they care about but do not have information on.

To identify the distribution of preferences, we follow the literature to 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)).[3] Hypothetical choice methods are attractive because they can allow unre-

[1] Manager heterogeneity also directly impacts workers' wages and wage inequality within firms (He & le Maire (2020), Acemoglu et al. (2022)).

[2] Becker (1971) conceptualized worker discrimination in the form of worker disutility from working for a specific group of employers. We extend the concept to incorporate worker beliefs and a tangible measure using compensating differentials in wages.

[3] Different workers may have different preferences on various dimensions of job attributes, many of which are unobservable to the researcher. Such preferences are very difficult to isolate using data on real-

stricted forms of preference heterogeneity (Blass, Lach & Manski 2010) while being able to hold fixed attributes not considered in the survey through instructions (Wiswall & Zafar (2018), Koşar, Ransom & Van der Klaauw (2021), Koşar, Şahin & Zafar (2021)) and to document strong correlation between stated and actual choices (Wiswall & Zafar (2018), Parker & Souleles (2019)).

To identify the distribution of beliefs, we embed a within-worker information experiment where we exogenously vary the observability of managerial ability. We define managerial ability as the manager's mentorship quality, motivated by a vast literature providing consistent evidence that mentorship has substantial positive impacts on human capital accumulation (Falk, Kosse & Pinger 2020), wage expectations (Boneva, Buser, Falk, Kosse et al. 2021), productivity (Blau, Currie, Croson & Ginther 2010), promotions (Lyle & Smith 2014), and the workforce composition of firms and can help minorities break through glass ceilings (Athey, Avery & Zemsky (2000), Müller-Itten & Öry (2022)).[4] We quantify mentorship of a manager as a rating on a five-point scale, motivated by a recent trend of rating managers and that firms care about these ratings (Cai & Wang 2022).[5]

We conduct this hypothetical choice survey and the information experiment among jobseeking students enrolled at a highly selective university who are one year away from graduating. 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 gender and manager mentorship quality) and cover the support of these attributes over the twenty different job choice scenarios.[6] In each scenario, respondents are asked to choose their most preferred job and then report the compensating differential in wages—a nonparametric cardinal measure—that would make them indifferent between the preferred job and the other jobs.

Extracting beliefs on manager quality through direct elicitation could be difficult, especially if we are concerned that the responses may be affected by social desirability bias.

ized job choices. However, data on realized job choices do have their own advantages, especially for helping us understand employer discrimination. This is because employers on average care about a consistent set of attributes in their workers.

[4]In the same spirit of in-group mentoring, through the American Economic Association's (AEA's) official mentoring program CeMENT, senior women faculty mentor junior women faculty.

[5]Many firms such as Google, e-Bay, and Amazon collect anonymous surveys from employees where they are asked to rate their managers. Comparably, Completed, TheJobCrowd and Kunukunu are some of notable start-ups that provide manager ratings analogous to Glassdoor's firm ratings.

[6]Conceptually, each hypothetical scenario could be thought of as a market. Choice in a market provides individual demand in that market. Survey data on choices over multiple scenarios varying attributes over their support allow 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 provide the identifying variation to estimate highly flexible models.

Hence, within the hypothetical job choice scenarios, we introduce a within-individual information experiment where we exogenously vary the observability of manager mentorship skill. The information experiment works as follows. In the first ten job choice scenarios, every individual observes three jobs in each scenario with different attributes: annual wages, flexibility of hours and manager name. As an attribute, mentorship is mentioned, but the data are shown to be unavailable. We call these first ten scenarios "incomplete scenarios" throughout the rest of the paper, given that the mentorship rating is not observable. In the last ten scenarios, individuals observe jobs with all of the above attributes as well as a manager mentorship rating. We call these last ten scenarios "complete scenarios". We elaborate 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 a willingness to forgo wages. Identification is achieved as follows. Each worker forms expected utilities while choosing a job. 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 the 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 that the reported compensating differentials only increase wages without changing anything else about the job.[7] Thus, the variation in compensating differentials within the complete scenarios identifies preferences. The variation in compensating differentials between the complete and incomplete scenarios resulting from the information experiment then isolates beliefs from preferences. Finally, with the preference and belief parameters identified for each worker, we can identify the corresponding distributions.

We find that in the absence of information on manager mentorship, such 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 skill, such 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 their average annual wages to work for female managers. Hence, in the

[7] This is one of the key advantages 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 closely these instructions are followed.

absence of information on manager quality, workers believe female managers to be worse mentors. We estimate the value of these negative beliefs on female managers' mentorship ability to be equivalent on average to 1.6% of workers' average annual wages.

An important finding from our within-worker information experiment is that there exists rich heterogeneity in the underlying distribution of worker preferences and beliefs on managers' gender and mentoring ability. Approximately 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 mentorship skill. Individuals majoring in engineering are more likely to prefer to work for female managers than those majoring in the humanities. Individuals whose mothers are weakly more educated than their fathers are less likely to have negative beliefs about female managers. We also find heterogeneity by the joint employment status of the individual's parents.[8] In general, such correlates of demographic characteristics with the estimates of beliefs could be useful in improving the design and efficiency of any policy targeted at removing information frictions.

In addition to our information experiment within the hypothetical choice survey, we collect further data to support our results. After the hypothetical choice scenarios, we ask questions that directly elicit respondents' beliefs. We ask respondents to report their expected mentorship rating of managers in ten hypothetical jobs while we exogenously vary manager names, flexibility of 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 evidence of average negative beliefs regarding female manager mentorship skill similar to what 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 skill when asked directly. This corroborating result tells us that the individual responses in our information treatment indirectly eliciting their beliefs are potentially robust to social desirability bias.

Our paper contributes to multiple strands of the literature. First, to the best of our knowledge, this is the first paper to provide evidence on the distribution of worker preferences and beliefs on manager gender and mentorship.[9] While Flory, Leibbrandt &

[8]Unlike Flory, Leibbrandt & List (2015) and Wiswall & Zafar (2018), we do not find evidence of differences in average preferences and beliefs by respondent gender which we discuss later.

[9]Recent work by Abel (2019), Abel & Buchman (2020) and (Ayalew, Manian & Sheth 2021) focus on how manager's achievements in their own jobs impact how likely workers are to follow their advice. Unlike the focus of this literature on managers' ability in their own job, our focus is on managers' mentorship quality, in view of the evidence on the significant impacts of managers' mentoring ability on their subordinates' labor market outcomes (Hoffman & Tadelis 2021) and the evidence for the Peter principle (Benson et al.

List (2015) find no evidence of a role of manager gender in application decisions, our analysis reveals that this finding is sensitive to the information that workers have about managers and that there exists substantial underlying heterogeneity in this regard. Second, the literature on discrimination usually deals with average discrimination driven by beliefs (statistical or biased beliefs) and by preferences (taste-based) separately (Charles & Guryan (2008), Guryan & Charles (2013), Lang & Lehmann (2012), Bertrand & Duflo (2017)). Kline, Rose & Walters (2021) estimate the distribution of racial discrimination, but they consider discrimination by firms toward workers. To the best of our knowledge, this paper is the first to explicitly allow for discrimination driven by both worker beliefs and preferences and to estimate their distributions. Our design generating unique panel data on compensating differentials allows us not only to test for belief-based discrimination (Altonji & Pierret (2001), Lange (2007), Agan & Starr (2018)) but also to quantify it (Bohren, Imas & Rosenberg 2019) as a measure of the willingness to forgo wages.[10]

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 other attributes are held fixed through instructions, with respect to various objects of choice: e.g., electricity services (Blass, Lach & Manski 2010), jobs (Wiswall & Zafar 2018), residential locations (Koşar, Ransom & Van der Klaauw 2021), political candidates (Delavande & Manski 2015), and insurance products (Boyer, De Donder, Fluet, Leroux & Michaud 2017). On this aspect, our paper is closest to Wiswall & Zafar (2018). We differ from this work by using an information experiment and eliciting wage compensating differentials between jobs instead of choice probabilities for each job. We formally show that using choice probabilities in contexts of both complete and incomplete scenarios cannot non-parametrically identify the distribution of the belief parameters. Given our design, reported compensating differentials allow us to jointly estimate the complete and incomplete scenarios to recover the distribution of preferences and beliefs. We can do this because the value of a dollar remains a dollar irrespective of whether the scenario is complete or incomplete. This allows us to directly estimate and interpret the preference and belief parameters as measures of willingness to forgo wages. Third, our question of interest involves identification of beliefs, similar to

2019)–namely, that high-ability workers, upon being promoted, do not necessarily become managers with high managerial ability.

[10] Bohren, Imas & Rosenberg (2019) additionally distinguish between discrimination resulting from correct beliefs and that resulting from incorrect beliefs in their experimental set-up studying the evolution of discrimination. We cannot take this route because we do not have access to data on the population distribution of mentorship quality that could provide the benchmark to test the hypothesis of biased beliefs against correct beliefs (statistical discrimination).

the setting of Adams-Prassl & Andrew (2019).[11] However, we differ by indirectly eliciting beliefs with our information experiment by using incomplete scenarios, thereby providing a new method for 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 survey that directly elicits beliefs to compare our results from the information experiment. We find that while the results are qualitatively similar, male respondents are more likely to shade down their negative beliefs on female manager mentorship skill when asked directly about their beliefs, relative to the beliefs elicited under our 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 on outcomes of mentees in academia, the corporate sector, the military and high schools (Athey, Avery & Zemsky (2000), Blau, Currie, Croson & Ginther (2010), Lyle & Smith (2014), Falk, Kosse & Pinger (2020), Müller-Itten & Öry (2022), 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 that jobseekers are willing to forgo to work for managers who are better mentors. We estimate that individuals are willing to forgo up to 5.65% of average annual wages for a one-standard-deviation increase in mentorship rating. This result is crucial to interpreting the beliefs on mentorship skill when it is unobservable to workers. If workers did not care about mentorship, then any belief distribution could rationalize the data, resulting in beliefs being fundamentally unidentified. Our job choice model incorporates this feature.

Finally, our work is also a part of the growing literature featuring online surveys and experiments (Stantcheva 2022) with information treatments for the study of beliefs (Wiswall & Zafar (2015), Kuziemko, Norton, Saez & Stantcheva (2015), Alesina, Miano & Stantcheva (2019), Boneva & Rauh (2018), Alesina & Stantcheva (2020), Stantcheva (2021), Alesina, Ferroni & Stantcheva (2021), Coibion, Gorodnichenko & Weber (2022)).

The paper is organized as follows: Section 2 provides details on the hypothetical job choice survey and 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 of how workers' preferences and beliefs drive their choices and compensating differentials. Section 5 shows identification using compensating differentials followed by non-identification if one were to use choice probabilities. Section 6 discusses estimation details and results. Section 7 presents the empirical distribution

[11]Beliefs in Adams-Prassl & Andrew (2019) are probabilities that individuals place on their own future outcomes, whereas in our paper, beliefs are workers' perceptions of potential managers' mentoring ability.

of beliefs and preferences and shows evidence on their underlying heterogeneity. Section 8 discusses the validity of the estimates of the belief parameters and further robustness checks. Section 9 discusses the importance of worker preferences and beliefs in tight labor markets along with potential avenues for future research. Section 10 concludes.

2 Institutional Context, Hypothetical Job Choice Survey and Information Experiment

We administered our hypothetical choice survey with the embedded information experiment to students of a highly selective public university in India who were one year away from graduating. The reason to sample from a highly selective university was to be able to draw from jobseekers who are likely to be high skilled, and as such whose turnover costs to firms would be high if they were to switch. This connects to the original motivation wherein firms might put larger weights on worker preferences if those workers are harder to replace. However, regardless of the skill of the jobseeker, their preferences and beliefs do matter for their job search and choice behavior. The reason to sample from an elite university in India is an advantage of an institutional feature of the recruitment process in elite institutions which by design usually reveals the gender of potential managers before a job match is actually formed. In most elite institutions in India "campus recruitment" is a common practice. Representatives of recruiting firms fly in to interview candidates on the university campus during their allotted date(s) and time slot(s). Campus recruitments usually involve multiple stages. The initial rounds consist of written aptitude tests. Upon qualifying in these initial rounds, the selected candidates move on to the final set of interview rounds. During these final rounds, the panel of interviewers is highly likely to also consist of the hiring manager(s) under whom they will be working, including others. This institutional feature provides us with a context where candidates are aware of the manager under whom they would be working initially in the firm. This reveals the gender of the manager to the job seeking candidate before accepting any job offer. Indeed, over time job switching and team switching within firm may occur. To avoid the effect of idiosyncratic experiences or shocks which lead to such switches we choose not to collect data from individuals who are currently in the labor market.

Our hypothetical job choice survey included the following sections in order (1) instructions to the respondents, (2) twenty hypothetical job choice and compensating differential *scenarios* within which the information experiment was embedded, (3) direct belief elicitation and (4) 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 exogenously varied attributes—manager name, annual wages, flexible hours and manager rating—of jobs shown to individuals in each job as shown verbatim in Figure 2.

It is important to highlight how we designed the scenarios to inform the respondents of the manager's gender and the manager's mentorship quality in each job option. We deliberately used managers' first names only. In the Indian context, last names can reveal caste and religion. Since we wanted to vary only the gender dimension, we did not show any last names, circumventing any potential concerns over differences in perceived gender roles across social classes. Thus the first names of managers used in our survey were directly indicative of only gender and did not vary in any other dimension. This setting is unlike the US context, where first names can be associated with both a race and a gender (e.g., Bertrand & Mullainathan (2004), Kline, Rose & Walters (2021)). Manager rating as an attribute is defined as "*... the average rating of the mentorship of the manager, provided by this manager's current employees in an anonymous survey. This is a measure of how good of a mentor this manager is this manager to its subordinates.*" followed by the description of the numeric five-point scale. Such anonymity in surveys is standard practice in the employee survey designs used on Amazon, Google and eBay.[12] Cai & Wang (2022) also use anonymous employee surveys in their field experiment to communicate employee feedback to treated teams' managers.

Survey instructions followed next, which facilitate identification using hypothetical choice data (Wiswall & Zafar (2018), Koşar, Şahin & Zafar (2021)). There were two key instructions in our survey, as shown verbatim in Figure 3. First, individuals were to assume that the jobs do not vary on any attribute "*...NOT MENTIONED...*" in the survey. Second, when asked to report the minimum increase in annual 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. We later reemphasized the instructions within each scenarios, as well. After the instructions, individuals were shown two example scenarios to familiarize them with the set-up before they started the main survey.

[12]We thank Will Dobbie for pointing this out.

2.2 Job choice scenarios with compensating differentials

Each *scenario* had two questions: a choice to be made among three hypothetical jobs, followed by a question on the compensating differentials that would make respondents indifferent between the jobs. Twenty such scenarios were administered in the survey to plausibly cover the support of job attributes, with the first 10 being the incomplete scenarios and the next 10 the complete scenarios.[13] We embedded the information experiment as follows: for every respondent, although the mentorship rating was mentioned as an attribute in all 20 scenarios, the first 10 scenarios (the incomplete scenarios) did not have rating data on the manager's mentorship ability, while the last 10 scenarios (the complete scenarios) did. Examples of job choice and compensating differential questions in both an incomplete scenario and a complete scenario are shown in Tables 1 and 2, respectively. Examples adapted to corresponding representative jobs in the USA are also shown in Appendix Tables A.1 and A.2.

Note that for the incomplete scenarios, the rating variable was mentioned but there were no ratings available for the managers. We had to ensure with regard to the wording that we neither primed individuals to think that the rating was indeed different across managers nor made them assume that the rating was the same across all managers. To achieve this, we used the following wording within each incomplete scenario: *"The rating of each manager may be different, but the data are not available."* We reemphasize that the jobs did not differ on *any other attribute not mentioned in the scenarios*. This is in line with the instructions shown at the start of the survey where respondents were instructed that the jobs do not vary on any attribute "*...NOT MENTIONED...*" in the survey.

In every scenario, after a job was chosen, the following question asked the respondents to report the compensating wage differentials for the jobs not chosen. For each unchosen job, respondents were asked to specify the minimum increase in annual wages that they would need to choose that job instead. These data provide us with the compensating wage differentials that would make the respondents indifferent between jobs. Individuals could report these on a slider scale that 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

[13] Ideally, we would have varied the job attributes along the full range of attributes, but this would have required asking a large number of questions, but only at a large cognitive cost to the respondents. Hence, to strike a balance between cognitive load and level of variation in job attributes, we chose to administer 20 scenarios. This choice was made after we observed the duration to completion and time spent on each question, especially the latter ones, in our pilots, which differed in the number of scenarios. Wiswall & Zafar (2018) have 16 scenarios. Koşar, Ransom & Van der Klaauw (2021) have three sets of 8, 16 and 24 scenarios.

they would need.[14]

In the 20 scenarios, there were 60 jobs, with half male and half female managers evenly distributed across the complete and the incomplete scenarios. Approximately half of the jobs had flexible hours, and the other half did not. The average annual wages were 7 lakh INR (≈ $ 39,444 in PPP). This was the average annual wages of jobs offered to past graduating cohorts of the university attended by the students in the sample. The variance in wages in the jobs that we showed was not particularly high. This mitigates any concerns that some jobs could be interpreted as entry-level and some as senior-level jobs. The average mentorship rating of managers in the complete scenarios was 3.41. In the results section, we use empirical evidence from our design to discuss the informativeness of the mentorship rating provided in our survey and mitigate potential concerns of other interpretations of mentorship that could have stemmed from not providing more context about the job(s).

We exogenously varied the attributes subject to the restriction that no job in each scenario was strictly dominant similar to Wiswall & Zafar (2018). Although our variation in job attributes was exogenous, it was deliberately not random in order to restrict scenarios being drawn with strictly dominant job options, as is standard in hypothetical choice surveys following Wiswall & Zafar (2018). In the model section we revisit this and explain its importance in connecting the assumptions of the model to the instructions which facilitates identification. Table 3 shows summary statistics of the attributes shown over the 60 jobs, Table 4 shows the overall balance of attributes between male and female managers, and Table 5 shows the balance of attributes in both complete and incomplete scenarios between male and female managers.

2.3 Direct belief elicitation

After the information experiment involving the 10 incomplete and 10 complete hypothetical job choice and compensating differentials scenarios, we also directly elicited beliefs on manager mentorship ability. We designed this component to allow us to compare our results on beliefs identified from the information experiment described above with those elicited by asking individuals directly. In this section, individuals were presented with 10 jobs with the manager's name, annual wages and availability of flexible hours. Individuals were were asked to report on a zero-to-five sliding scale the manager mentorship ratings that they expected to be associated with each job, as shown in Figure 7.

[14] We did not find any evidence of any design-induced bunching of reported compensating differentials at the boundary of the slider at 2 lakhs INR (≈ 2857 USD). We thank Jeff Smith for bringing our attention to check this.

2.4 Demographic questions

The final section of our survey asked the respondents demographic questions on their area of study (arts, science or engineering), family income, parental education and occupation. Then, we asked questions specifically designed to allow us to infer whether they had followed our instructions. The survey ended with the choice of mode of online payment for completing the survey.

2.5 Key highlights of the design

In this section, we highlight some of the important aspects of the design of the hypothetical job choice survey and the way in which the embedded information experiment enables us to identify beliefs and preferences from the reported choices and compensating differentials, given the instructions.

We deliberately used managers' first names only. In the Indian context, last names can reveal caste and religion. Since we wanted to vary only the gender dimension, we did not show any last names, circumventing any potential concerns over differences in perceived gender roles across social classes. Thus the first names of managers used in our survey were common names and were directly indicative of only gender and did not vary in any other dimension. This setting is unlike the US context, where first names can be associated with both a race and a gender (e.g., Bertrand & Mullainathan (2004), Kline, Rose & Walters (2021)).

By construction, the ability to observe the entire choice set is one of the key advantages of our design. We observe which jobs are chosen and which jobs are not. Additionally, we observe the compensating differentials that make individuals indifferent across all choices in the choice set. This gives us a nonparametric cardinal measure of utilities and thus allows us to avoid making any distributional assumptions on the preference or belief parameters.

The data on the compensating differentials that make individuals indifferent between jobs allow us to directly estimate and interpret the parameters as measures of willingness to pay or to forgo wages.[15]

The information treatment is given to every individual. For each individual, we observe the sequence of choices made and the compensating differentials reported over the incomplete scenarios and then over the complete scenarios. This allows us to uncover the distributions of preferences and beliefs and not just the first moment, which would have

[15] This is also possible with data on choice probabilities but requires an additional step to transform the estimates into willingness-to-pay measures. See Wiswall & Zafar (2018).

been the case had we provided the information treatment to a 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. Our concerns over the potentially high cognitive load associated with making choices among a large number of options led us to conclude that it was infeasible to ask individuals to choose among a large number jobs within each scenario. Hence, we did this over a panel of scenarios, making them choose and provide compensating differentials over three jobs per scenario. This generated panel data on choices and compensating differentials over jobs that exogenously vary in attributes. Later in the paper we formally visit the discussion on why we did not use choice probabilities in our context of complete and incomplete scenarios.

3 Data

We collected data in the second week of April 2020, using an online survey administered to students of a highly selective public university in India. A key feature of elite universities in India is the campus recruitment system wherein current firm employees including managers and at times vice-presidents, arrive at the campuses of these universities to interview and recruit students who are about to graduate and are on the job market. In this system, job-seekers are highly likely to be interviewed by the potential manager at advanced stages of the hiring process. This reveals the gender of the potential manager during the hiring process to the job-seeker.

Students eligible to participate in the survey were only those at most one year away from graduating.[16] Upon completion of the survey, participants were paid INR 500 ($\approx$ \$24 in PPP[17]) through their preferred online payment mode. See Appendix A.6 for further details on the administration and implementation of the survey.

3.1 Sample selection and description

The total number of participants in our survey was 604, among which 591 completed the survey. Out of these, we dropped 11 respondents who could not be verified as students

[16] In 2020, the total number of enrolled students in the university was 11,064. Out of these, 6,283 were enrolled in undergraduate programs, 2,588 in master's programs, and the remaining 1,193 in MPhil and PhD programs.

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

or completed the survey in less than 15 minutes or both.[18] The median time to survey completion was 51.37 minutes. This brought our final sample size to 580.

Table 6 reports sample descriptives. A total of 41.72% of our sample consisted of female students, and the remaining 58.28% were male students.[19] With respect to majors, 44% were enrolled in a department in the arts faculty, 33.28% in engineering, and the remaining 22.07% in science. Female students were predominantly arts students (67%). Men were predominantly engineering (49%) and science (33%) students.

3.2 Patterns in the raw data

In this subsection, we explore how individuals' choices and reported compensating differentials varied across the complete and incomplete scenarios between jobs with male and female managers. This section is an important precedent to the section where we structure our data to rationalize them in a model involving preferences and beliefs.

Table 7 reports the percentage of jobs chosen by manager gender in both the complete and incomplete scenarios. The first observation is that between male and female respondents, the percentages of jobs chosen with managers of the two genders do not differ substantively. Furthermore, in the absence of information on mentorship ability (in the incomplete scenarios), the percentage of jobs with female managers chosen was not that different from that of jobs with male managers. However, we observe that in the complete scenarios, upon revelation of the manager mentorship information, the percentage of jobs with female managers chosen is 61.1%, which is approximately 20 percentage points higher than that of jobs with male managers.

Table 8 reports the average compensating differentials reported for unchosen jobs with male and female managers and the difference between them along with the associated standard errors and standardized differences. The table reports these numbers separately for the complete and incomplete scenarios. We observe that in the absence of information on manager mentorship skill, individuals on average report compensating differentials required to choose jobs with female managers over jobs with male managers that are higher by 6.3 thousand INR ($\approx$ \$ 300). However, this result flips in the complete scenarios. When provided information on the mentorship rating, individuals on average demand 6.1 thousand INR ($\approx$ \$ 290) more for unchosen jobs with male managers. Both differences are statistically significant at the 99% level. We should maintain caution in interpreting these numbers because they compare compensating differentials among the set

[18] The first percentile of duration to survey completion was at 13.89 minutes.

[19] In the survey, we asked individuals their biological sex. We did not ask about gender identifications not coinciding with biological sex.

of jobs not chosen. Nevertheless, these numbers provide useful information on the set of unchosen jobs. A more informative way to understand the compensating differential data would be to incorporate the choices made (the extensive margin) and the compensating differentials for the jobs not chosen (the intensive margin) conditional on job attributes. This is what we do in the job choice model. The estimates from our model—as we will show and discuss in subsequent sections—will reveal a very similar overall pattern and corresponding conclusions, as is observed in the patterns in the raw data given our exogenous variations of attributes.

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 women are more likely than men to choose jobs with female managers. This can be answered with data from the complete scenarios using a simple difference-in-differences estimation strategy. We do not include the incomplete scenario data here because we do not want to deal with the omitted variable bias that would arise from how individuals form beliefs on mentorship skill, which they do not observe in the incomplete scenarios.

Individuals are indexed by $i = 1, .., N$ and jobs by $j = 1, .., J$. Define $Choice_{ijs}$ as an indicator variable which takes value 1 if individual i in scenario s chooses 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 the gender of the manager in job j of scenario s by $MG_{j(s)}$. $Attributes_{j(s)}$ is the vector of job attributes associated with job j in scenario s other than manager gender, i.e., annual wages, flexibility of hours and mentorship skill of the manager. $Demographics_i$ is a vector of the individual-level demographics described in the previous section. Our specification includes scenario fixed effects λ_s to leverage the variation in choices made within scenarios resulting from the variation in attributes between jobs within each scenario. We estimate this difference-in-differences equation with a logit model and bootstrap the standard errors at the individual level.

Table 9 shows the marginal effect estimates from equation (1). We find no evidence that female workers are more likely than male workers to choose jobs with female managers. Note 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 the complete (or incomplete) scenarios. As one would expect, higher wages, availability of flexible hours and better mentorship are associated with a higher likelihood of a job 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 but also incorporate the data on compensating differentials. We do this through the lens of worker preferences and the way beliefs operate in the absence of information on manager mentorship skill. The model also allows us to estimate our parameters as percentages of average annual wages to provide a better interpretation of their importance.

4 Model

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

$$U_{ij} = u_i(X_j) + \epsilon_{ij} \tag{2}$$

where ϵ_{ij} denotes all unobservables that affect the utility of individual i from job j. Individuals form expected utilities while reporting their job choice and the corresponding compensating differentials that would make them indifferent between jobs in expectation.

Individuals have preferences over working for a male manager (G), annual wages (W), availability of flexible hours (H) and manager mentorship rating (R). We denote this set of attributes as $X \equiv \{G, W, H, R\}$. In the complete scenarios, respondents observe X for each job. In the incomplete scenario, respondents observe $\tilde{X}$, where $\tilde{X} \equiv X \setminus R$. In the incomplete scenarios, when individuals do not observe the mentorship rating R, they use their beliefs on R given $\tilde{X}$ to form their expected utilities.

The model is nonparametrically identified up to the distribution of $\epsilon_i \equiv \{\epsilon_{i1}, \ldots, \epsilon_{iJ}\}$, as shown in Appendix A.1. In the following sections, to keep things simple, we use a linearly separable model.

The 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

$$U_{ij} = X_j'\beta_i + \epsilon_{ij} \tag{3}$$

Identification of more variants of the model allowing for various interactions is shown in Appendix A.3 and monotone transformations is shown in Appendix A.4.

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

$$\mathbb{E}_i[U_{ij} \mid X_j] = X_j'\beta_i + \mathbb{E}_i(\epsilon_{ij} \mid X_j) \tag{4}$$

The preference parameters of individual i is given by the vector $\beta_i \equiv (\beta_i^G, \beta_i^W, \beta_i^H, \beta_i^R)'$. We assume that each individual i knows their preferences β_i^x for each attribute $x \in X \equiv \{G, W, H, R\}$ and hence do not take expectations over them. As explained above, this draws a clear parallel with asking for choices instead of choice probabilities.

4.2 Incomplete scenarios

In the incomplete scenarios, the rating of the manager is mentioned but the data are shown as unavailable to the respondents. Hence, respondents form expectations over them in reporting their choices and compensating differentials, conditional on the attributes they observe in the incomplete scenarios. Denote the set of observable attributes in job j as $\widetilde{X_j} \equiv X_j \setminus \{R_j\}$ in the incomplete scenarios.

Individual i does not observe R_j and uses $R_j = \widetilde{X_j}'\alpha_i^x + \eta_j$ to form their beliefs where η_j could be interpreted as measurement error. Consequently, individual i forms expectations on the mentorship of the manager in the associated job as

$$\mathbb{E}_i(R_j \mid \widetilde{X}_j) = \widetilde{X}_j'\alpha_i \tag{5}$$

The belief parameters of individual i are given by the vector $\alpha_i \equiv (\alpha_i^G, \alpha_i^H, \alpha_i^W)'$. We assume that all individuals know their belief parameters α_i^x for each attribute $x \in \widetilde{X} \equiv X \setminus \{R\}$ and hence do not take expectations over them. Observe that $\alpha_i^G = \mathbb{E}_i(R \mid G = male, W, H) - \mathbb{E}_i(R \mid G = female, W, H)$ represents how much on average individual i believes a male manager's mentorship rating differs from that of a female manager. It is important to emphasize that the expectations here are allowed to vary by individuals. This allows individuals to draw from different distributions of mentorship, which may not necessarily be the true distribution. Also note that linear separability of the belief function is a simplifying assumption which does not aide in identification.[20] Indeed, we could allow for and identify parameters on various interactions among the attributes $\widetilde{X_j} \equiv X_j \setminus \{R_j\}$ observable in the incomplete scenarios. As number of scenarios in both the complete and incomplete scenarios approach infinity we could allow for a fully non-parametric belief function.

The expected utility of individual i from job j conditional on its observable attributes $\widetilde{X_j}$ in the incomplete scenarios is given by

$$\mathbb{E}_i[U_{ij} \mid \widetilde{X}_j] = \sum_{x \in \widetilde{X}} \beta_i^x x_j + \beta_i^R \mathbb{E}_i(R_j \mid \widetilde{X}_j) + \mathbb{E}_i(\epsilon_{ij} \mid \widetilde{X}_j) \tag{6}$$

Simplifying the expected utilities in the incomplete scenarios given the belief function we have,

$$\mathbb{E}_i[U_{ij} \mid \widetilde{X}_j] = \sum_{x \in \widetilde{X}} (\beta_i^x + \beta_i^R \alpha_i^x) x_j + \mathbb{E}_i(\epsilon_{ij} \mid \widetilde{X}_j) \tag{7}$$

Denote for each attribute $x \in \widetilde{X} \equiv \{G, W, H\}$ and each individual i

$$\widetilde{\beta}_i^x \equiv \beta_i^x + \beta_i^R \alpha_i^x \tag{8}$$

Observe that $\widetilde{\beta}_i^x$ is comprised of two terms: the preference parameter β_i^x for attribute x and how much x affects the belief about the manager's rating α_i^x, weighted by how much the individual cares about the manager's rating β_i^R.

5 Identification

In this section, we show how our experimental panel data on choices and compensating differentials identify the preference and belief parameters of our model of job choice by exploiting variation in the reported compensating differentials within and between the complete and incomplete scenarios.[21]

The verbatim instructions given to respondents are shown in Appendix Table 3. Through the instructions, individuals were instructed to assume that

[20] We thank the suggestion of an anonymous referee to make this point explicit.

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

Assumption (1): All attributes not mentioned in the survey were the same for all jobs.

Assumption (2): The reported compensating differential would increase only wages and change nothing else about the job.

Observe that instruction 1 is an assumption between jobs, while instruction 2 applies within jobs. The purpose of these instructions was to ensure that there was no selection on attributes not mentioned in the survey. Wiswall & Zafar (2018) delineate the importance of assumption (1) in a set-up such as our own in contrast to the settings in audit studies on hiring discrimination, where there is little preventing employers from making different assumptions about different job applicants conditional on the observables in their resumes.[22] Additionally, Wiswall & Zafar (2018) explain that assumption (1) via the instructions avoids biases that could arise from omitted variables through unobservables or from potential equilibrium effects in realized choice data. For both scenarios, assumption (2) implies that the compensating differential increases only 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 manager rating as well, as we show in the following sections. We use the data on compensating differentials to equate the expected utilities in the complete and incomplete scenarios. These two assumptions, which form a clear parallel to the instructions given to the respondents, form the basis of our identification strategy.

5.1 Identification of preferences from the variation within the complete scenarios

In this section, we show the identification of the preference parameters β_i^x for all $x \in \{G, H, R\}$ as defined in equation 4. The parameter of interest is β_i^G, which is the preference for male managers over female managers. We use assumptions (1) and (2) to identify the preferences using the 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,

[22] For more on the use of audit studies in detecting discrimination, see Heckman (1998) and related papers within it.

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

Implication of Assumption (2):

In the complete scenarios, for each job k, individuals observe the vector of attributes $X_k \equiv \{G_k, H_k, W_k, R_k\}$. Suppose that individual i chooses job j and then provides a compensating differential of Δ_{ijk} that she would require to choose job k instead. The instructions imply that for unchosen jobs such as job k,

$$\mathbb{E}_i(\epsilon_{ik} \mid X_k, \Delta_{ijk}) = \mathbb{E}_i(\epsilon_{ik} \mid X_k) \tag{9}$$

Given the above, equating the expected utilities between job j and job k with the provided compensating differential of Δ_{ijk} and normalizing $\beta_i^W = 1$, we have

$$\begin{gathered}\mathbb{E}_i(U_{ij} \mid X_j) = \mathbb{E}_i(U_{ik} \mid X_k, \Delta_{ijk}) \\ \Delta_{ijk} = (X_j - X_k)'\beta_i\end{gathered} \tag{10}$$

Thus, the preference parameters $\{\beta_i^G, \beta_i^H, \beta_i^R\}$ are identified using the variation in the reported compensating differentials in the complete scenarios under assumptions (1) and (2) .

5.2 Identification of beliefs from the variation between the complete and incomplete scenarios

Now, we turn to the incomplete scenarios in conjunction with the complete scenarios and show the identification of the belief parameter vector $\alpha_i \equiv (\alpha_i^G, \alpha_i^H, \alpha_i^W)'$ for each individual i, exploiting the variation between the reported compensating differentials between the complete and 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,

$$\mathbb{E}_i(\epsilon_{ij} \mid \widetilde{X}_j) = \mathbb{E}_i(\epsilon_{ik} \mid \widetilde{X}_k)$$

Implication of Assumption (2):

In the incomplete scenarios, for each job k, individuals observe the vector of attributes $\widetilde{X}_k = \{G_k, H_k, W_k\}$. Suppose that individual i chooses job j and provides a compensating differential of $\widetilde{\Delta}_{ijk}$ that she would require to choose job k instead. All the compensating differential does is increase the wages in job k by $\widetilde{\Delta}_{ijk}$. 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,

$$\mathbb{E}_i(R_k \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) = \mathbb{E}_i(R_k \mid \widetilde{X}_k) \tag{11}$$

Thus, the expected utility from job k taking into account the compensating differential of $\widetilde{\Delta}_{ijk}$ along with the normalization of β_i^W to 1 is

$$\begin{aligned}
&\mathbb{E}_i(U_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) \\
&= \beta_i^G G_k + \beta_i^H H_k + (W_k + \widetilde{\Delta}_{ijk}) + \beta_i^R \mathbb{E}_i(R_k \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) + \mathbb{E}_i(\epsilon_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) \\
&= \beta_i^G G_k + \beta_i^H H_k + (W_k + \widetilde{\Delta}_{ijk}) + \beta_i^R \mathbb{E}_i(R_k \mid \widetilde{X}_k) + \mathbb{E}_i(\epsilon_{ik} \mid \widetilde{X}_k) \\
&= \sum_{x \in \widetilde{X}} (\beta_i^x + \beta_i^R \alpha_i^x) x_k + \widetilde{\Delta}_{ijk} + \mathbb{E}_i(\epsilon_{ik} \mid \widetilde{X}_k)
\end{aligned} \tag{12}$$

given beliefs about mentorship in equation (5).

Individuals are assumed to know their preference parameters and hence not to take expectations over them. We can normalize $\beta_i^W = 1$ as discussed before, because the valuation of a dollar remains a dollar irrespective of whether the scenario is complete or incomplete. Equating the expected utilities between job j and job k with the provided compensating differential of $\widetilde{\Delta}_{ijk}$ under A1, we have

$$\begin{aligned}
\mathbb{E}_i(U_{ij} \mid \widetilde{X}_j) &= \mathbb{E}_i(U_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) \\
\widetilde{\Delta}_{ijk} &= \sum_{x \in \widetilde{X}} \underbrace{(\beta_i^x + \beta_i^R \alpha_i^x)}_{\widetilde{\beta}_i^x} (x_j - x_k)
\end{aligned} \tag{13}$$

Now, identification of α is straightforward. Recall, we denoted for each attribute $x \in \widetilde{X}$

$$\widetilde{\beta}_i^x \equiv \beta_i^x + \beta_i^R \alpha_i^x \tag{14}$$

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

$$\alpha_i^x = \frac{\widetilde{\beta}_i^x - \beta_i^x}{\beta_i^R} \tag{15}$$

Thus, α_i^x is identified $\forall x \in \widetilde{X}$ 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 (10) and (13) on compensating differentials in the complete and incomplete scenarios respectively.

In the complete scenarios, the compensating differentials are a function of how jobs j and k vary in their attributes, weighted by how much individual i cares about each of those attributes. In contrast, in the incomplete scenarios, they are a function of how jobs j and k vary in their attributes apart from mentorship, weighted by not only how much individuals care about each attribute but also by how much they believe each attribute is correlated with mentorship skill—very much in the spirit of omitted variable bias.

Additionally, note that there are two circumstances when beliefs 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 ability. The underlying intuition is that if individuals do not care about manager mentorship, 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 skill. Secondly, beliefs are not identified if individuals believe mentorship ability is independent of all observed attributes. In particular, in that case, we would have for each individual i, $\mathbb{E}_i(R_k \mid \widetilde{X}_k) = \mathbb{E}_i(R_k)$ for all jobs k, which is a constant, though it could vary by i. However, since it does not vary with the observed job attributes, any within-individual variation cannot be used to identify beliefs.

5.3 Non-identification with choice probability data

Before we delve into the estimation details of our model and the results, it is important to explain why we did not use choice probabilities.[23] The hypothetical choice methodology literature has focused primarily on asking for respondents' choice probabilities if they were presented with a given choice at some point in the future. Asking for probabilities implies resolution of resolvable uncertainty (Blass, Lach & Manski 2010). Hence, asking for probabilities makes sense only when individuals are asked about future choices, and it is the resolvable uncertainty between today and the future that is the source of these probabilities. The model takes as given that individuals know their preferences and the unobservables are interpreted as taste shocks. Any uncertainty that could arise from individuals learning about their preferences over time (Delavande & Manski 2015) is implicitly assumed away.[24] The remaining unobserved uncertainties that affect utility are instructed to be held fixed across potential choices. The identification assumption is that these unobserved uncertainties are additively separable and independent of the

[23] We thank the suggestion of an anonymous referee to formally explain the reason.

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

exogenously varied attributes of interest. However, note that all such estimations are in contexts wherein individuals observe all relevant attributes of interest for all potential choices, that is in contexts of "complete scenarios" only, in our terminology. In this subsection, we formally show why using elicited choice probabilities in contexts of both complete and incomplete choice scenarios such as ours cannot identify the distribution of the belief parameters.

Imagine a set-up of complete and incomplete scenarios identical to ours, except where respondents are asked for choice probabilities, instead of making a choice and reporting compensating differentials for the other options. Utility of individual i from job j is given by $U_{ij} = X_j'\beta_i + \epsilon_{ij}$ where X_j consists of the exogenously varied relevant job attributes and β_i is the preference parameter vector of individual i. In the survey asking for choice probabilities, individuals are instructed to imagine themselves making a job choice some years into the future, and correspondingly report probabilities today. Hence, the vector of error terms $\epsilon_i \equiv \{\epsilon_{i1}, \dots, \epsilon_{iJ}\}$ has the interpretation of resolvable uncertainty as in Blass, Lach & Manski (2010). The usual assumption is that these unobserved resolvable uncertainties ϵ_i are independently and identically distributed across individuals following Type I extreme value distribution without loss of generality (McFadden & Train 2000). Given the instructions, for each individual i, the additively separable unobserved resolvable uncertainties ϵ_i are independent of the exogenously varied X_j (Wiswall & Zafar 2018).

Denote p_{ij} as the probability of individual i choosing job j in a complete scenario while observing all the attributes $X_j \equiv \{G_j, W_j, H_j, R_j\}$, and $\widetilde{p_{ij}}$ as the probability of choosing job j in an incomplete scenario while observing $\widetilde{X_j} \equiv X_j \setminus \{R_j\}$. With the assumption of the unobservable part of the utility function consisting of resolvable uncertainty ϵ_{ij} is i.i.d. Type I extreme value distribution, we can write the probability of individual i choosing job j in the complete scenarios observing all the relevant attributes X_j as,

$$p_{ij} = \frac{exp(X_j'\beta_i)}{\sum_j exp(X_j'\beta_i)}$$

Note that in writing the choice probability like above requires the normalization of the variance of the error term as is standard in discrete choice models. However, in the incomplete scenarios individuals observe $\widetilde{X_j}$. Individuals do not observe R_j and use $R_j = \widetilde{X_j}'\alpha_i^x + \eta_j$ to form their beliefs where η_j could be interpreted as measurement error. In the incomplete scenarios, the probability of individual i choosing job j over job k for all jobs $j \neq k$ can be written as:

$$
\begin{aligned}
\widetilde{p_{ij}} &= Pr(U_{ij} > U_{ik}) \\
&= Pr\left(\sum_{x\in\widetilde{X}} \beta_i^x x_j + \beta_i^R R_j + \epsilon_{ij} > \sum_{x\in\widetilde{X}} \beta_i^x x_k + \beta_i^R \eta_k + \epsilon_{ik}\right) \\
&= Pr\left(\sum_{x\in\widetilde{X}} (\beta_i^x + \beta_i^R \alpha_i^x) x_j + \beta_i^R \eta_j + \epsilon_{ij} > \sum_{x\in\widetilde{X}} (\beta_i^x + \beta_i^R \alpha_i^x) x_k + \beta_i^R \eta_k + \epsilon_{ik}\right) \\
&= Pr\left(\beta_i^R(\eta_j - \eta_k) + \epsilon_{ij} - \epsilon_{ik} > \sum_{x\in\widetilde{X}} (\beta_i^x + \beta_i^R \alpha_i^x)(x_k - x_j)\right)
\end{aligned}
$$

Observe that calculating this choice probability requires the researcher to normalize of the variance of the error term in this incomplete scenario which is $\beta_i^R \eta_j + \epsilon_{ij}$, on top of the above normalization of the variance of ϵ_{ij}. The requirement of having to normalize two variances makes one of the normalizations non-innocuous. This is the primary disadvantage of using choice probabilities in contexts such as ours where the individuals make choices in both complete and incomplete scenarios. It is important to highlight that even parametric assumption on the distribution of η will not achieve identification. For the purpose of illustration and simplicity, let us assume that both error terms follow normal distributions.[25] In particular, let us assume that

$$\epsilon_i \overset{\text{iid}}{\sim} N(0, \sigma_\epsilon^2)$$

and

$$\eta_j \overset{\text{iid}}{\sim} N(0, \sigma_\eta^2)$$

with $\epsilon_i \perp \eta_j$ for all i and j. Given this we have,

$$\beta_i^R \eta_j + \epsilon_{ij} \overset{\text{iid}}{\sim} N(0, \sigma_\epsilon^2 + (\beta_i^R \sigma_\eta)^2)$$

With choice probabilities reported in the complete scenarios it is easy to show that as number of complete and incomplete scenarios go to infinity one can identify for all individuals i the following parameters from the complete scenarios

[25]If we proceeded with the assumption of ϵ_i following Type-I extreme value, for any distribution of η_j the distribution of $\beta_i^R \eta_j + \epsilon_{ij}$ obtained by convolution would no longer follow a Type I extreme value distribution. Consequently, the differences would no longer follow a logistic distribution, and we will lose the convenience of the closed form solution which is helpful for the purposes of illustration.

$$\left\{\frac{\beta_i^x}{\sigma_\epsilon}\right\} \quad \forall x \in X \equiv \{G, W, H, R\}$$

and for all individuals i, the following parameters from the incomplete scenarios

$$\left\{\frac{\beta_i^x + \beta_i^R \alpha_i^x}{\sqrt{\sigma_\epsilon^2 + (\beta_i^R \sigma_\eta)^2}}\right\} \quad \forall x \in \widetilde{X} \equiv \{G, W, H\}$$

From the above it is easy to see that the belief parameters α_i^x are not identified without non-innocuous normalizations of the variance terms. Even with the distributional assumption on η the only way to achieve identification of the belief parameters will require the knowledge of σ_η. To see this observe that for all $x \in \widetilde{X} \equiv \{G, W, H\}$ we can rewrite $\left\{\frac{\beta_i^x + \beta_i^R \alpha_i^x}{\sqrt{\sigma_\epsilon^2 + (\beta_i^R \sigma_\eta)^2}}\right\}$ as

$$\left\{\frac{\frac{\beta_i^x}{\sigma_\epsilon} + \frac{\beta_i^R}{\sigma_\epsilon}\alpha_i^x}{\sqrt{1 + \left(\frac{\beta_i^R}{\sigma_\epsilon}\sigma_\eta\right)^2}}\right\} \quad \forall x \in \widetilde{X} \equiv \{G, W, H\}$$

With $\left\{\frac{\beta_i^G}{\sigma_\epsilon}, \frac{\beta_i^W}{\sigma_\epsilon}, \frac{\beta_i^H}{\sigma_\epsilon}, \frac{\beta_i^R}{\sigma_\epsilon}\right\}$ identified for all individuals i from the complete scenarios, the only unknown terms in the above expression for all individuals i are the set of belief parameters $\{\alpha_i^G, \alpha_i^W, \alpha_i^H\}$ and σ_η.

Note that if we were dealing with complete scenarios only and did not have any incomplete scenarios, there is no clear advantage of using compensating differentials over choice probabilities as both provide the researcher with cardinal information on preferences.[26]

This problem of non-identification of belief parameters using choice probability data, also persists with rank data. This is because it follows similar steps after specifying a distribution of the unobserved part of the utility function. Thus, it is the combination of complete and incomplete scenarios that requires us to use compensating differentials. Using compensating differentials aides in identification because the value of a dollar always remains a dollar irrespective of the type of scenario.

[26]Using rank data is always dominated—even in complete scenarios—because cardinal information provides more information on the distribution of preferences to the researcher than ordinal information from ranks.

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 the reporting of the 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 their 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. If both types of measurement errors are classical in nature, they will only inflate the standard errors. The consistency of the estimates is not affected.

Denote as Δ^*_{ijk} and $\widetilde{\Delta}^*_{ijk}$ the latent compensating differentials and as e_i and $\widetilde{e}_i$ the composite classical measurement errors in the complete and 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 scenario:

$$\begin{aligned} \Delta^*_{ijk} &= \sum_{x \in X} \beta^x_i (x_j - x_k) + e_i \\ \widetilde{\Delta}^*_{ijk} &= \sum_{x \in \widetilde{X}} (\beta^x_i + \beta^R_i \alpha^x_i)(x_j - x_k) + \widetilde{e}_i \end{aligned} \tag{16}$$

With classical measurement errors, we have

$$\begin{aligned} \mathbb{E}[\Delta^*_{ijk} \mid X_j, X_k] &= \sum_{x \in X} \beta^x_i (x_j - x_k) = (X_j - X_k)'\beta_i \\ \mathbb{E}[\widetilde{\Delta}^*_{ijk} \mid \widetilde{X}_j, \widetilde{X}_k] &= \sum_{x \in \widetilde{X}} (\beta^x_i + \beta^R_i \alpha^x_i)(x_j - x_k) = (\widetilde{X}_j - \widetilde{X}_k)'\tilde{\beta}_i \end{aligned} \tag{17}$$

We jointly estimate the above system of equations (16) 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 block bootstrap at the respondent level to allow for arbitrary correlation among responses within each respondent. We describe the details of the joint estimation and the bootstrap algorithm in Appendix A.2.

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. Estimates of alternate models allowing for nonlinearities, presented in Appendix A.3, have similar results and are presented in the Online Appendix. In the first subsection, we discuss the estimates for preference parameters focusing on the preference on manager gender. Next, we discuss the preference and thus demand for good mentors. We discuss estimates of the belief parameters focusing on beliefs on mentorship ability by manager gender in the final subsection. This order of discussion is deliberate because only after establishing how much individuals care about managers' gender and mentorship skill is it useful to discuss beliefs on mentorship by manager gender.

Since the utility parameter on wages is normalized to 1 and wages are in units of hundred thousand INR, the estimates should be interpreted as valuations of each attribute in units of hundred thousand INR.[27] However, for even better interpretability, we also present these estimates by converting them into percentages of average annual wages.

6.1.1 Preference for working for female managers

Table 10 shows the estimates from equation system (16) representing indifferences in the complete and incomplete scenarios jointly exploiting the variation in reported compensating differentials across jobs with exogenously varying attributes. We first discuss the complete scenarios, from which we derive the pure preference parameter estimates on manager gender, flexibility of hours and manager mentorship rating, with the preference parameter on average wages normalized to 1.

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[28] of this value as a percentage of average annual wages is from 1.3% to 2.2%.

For the incomplete scenarios, the "biased" estimate of the preference for male managers ($\tilde{\beta}^G$) is statistically indistinguishable from zero. The difference in the estimates across the complete (β^G) and incomplete scenarios ($\tilde{\beta}^G$) provides evidence that in the absence of information on manager mentorship quality, individuals believe that male managers are better mentors. The results show that beliefs and preferences operate in opposite directions to generate these indifferences. This difference in the estimates between the complete and incomplete scenarios is evidence of belief-based discrimination against female managers if and only if individuals prefer to work for managers who are

[27] Alongside the estimates, we present the purchasing power parity equivalent in USD.

[28] Bias-corrected bootstrap confidence interval.

better mentors. We now turn to discussing preferences on manager mentorship ability.

6.1.2 Demand for mentorship quality in managers

As explained earlier in the identification section, if individuals do not care about manager mentorship (i.e., $\beta^R = 0$), then beliefs are fundamentally unidentified, and thus, this difference cannot be taken as evidence of belief-based discrimination. Table 10 shows that respondents care about high-quality mentorship from their managers. Individuals on average are willing to give up approximately 11% of their average annual wages ($\approx$ \$3,800 or 80 thousand INR) to work for a mentor who ranks one point higher in mentorship ability on a five-point scale. Converting this to standard-deviation units, given the variation in mentorship ratings in the scenarios presented to the respondent, a one-standard-deviation increase in mentorship skill is valued at 5.65% of average annual wages. This estimate could seem large at first glance. However, it is not surprising given that the respondents are jobseekers who are about to enter the labor market for the first time. Under diminishing returns to mentorship, a marginal increase in mentorship ability is of much higher value to first-time jobseekers than to experienced workers in the labor market.

A potential concern could revolve around whether the mentorship rating was at all informative to the respondents.[29] Recall that the mentorship rating was presented in the survey as the "*... the average rating of the mentorship of the manager, provided by this manager's current employees in an anonymous survey*". Even though our scenarios in the survey do 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, or different types of jobs, such that the mentorship quality rating was uninformative, then we would observe evidence of this in the data. By contrast, the lower limit of the 95% confidence interval on the preference for high-rated mentors is at 10.5% of average annual wages, far from zero. The detailed instructions and the evidence mitigate concerns of mentorship rating provided in the survey being uninformative to the respondents.[30]

6.1.3 Beliefs

The estimates of the belief parameter on male managers' mentorship (α_i^G) are obtained from the estimates of the vectors $(\widetilde{\beta}_i^G, \beta_i^G, \beta_i^R)$ using equation (15). Table 11 shows that on

[29] A real world example could be a woman evaluating a job offer from the construction sector, which is heavily male-skewed.

[30] There is less concern about other interpretations of mentorship. For example, it is unlikely that English majors would answer our questions by invoking upon themselves the extra cognitive load to think about jobs outside their domain of specialization.

average male managers are believed to have a 0.14 points (on a 5-point scale) or 0.28 standard deviations higher mentorship rating than female managers. Classical measurement error in the reported compensating differentials leading to inflation of standard errors in the estimation of the preference parameters will trickle down to the standard errors of the belief parameters. Despite this, the belief parameter estimate is statistically significant. The estimates in conjunction with the model and the evidence that mentorship skill is a highly sought-after manager attribute imply that in the absence of a manager rating, both genders believe that male managers are better mentors than female managers.

The estimates of α_i^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 valuation of beliefs on male manager mentorship ($\beta_i^R \alpha_i^G$). In Table 12, we report these estimates of the valuation of worker beliefs. Observe that the difference in the parameters between the complete and incomplete scenarios provides us exactly that: $\tilde{\beta}_i^x - \beta_i^x = \beta_i^R \alpha_i^x$ for all $x \in \{G, W, H\}$. Thus, the estimates of $\beta_i^R \alpha_i^G$ provide us an estimate of the valuation of beliefs on male managers' mentorship relative to female managers.[31]

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 the standard errors of the mean. More interestingly, however, 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

[31] In addition, note that $\frac{\mathbb{E}(\tilde{\beta^G}_i - \beta_i^G)}{\mathbb{E}(\beta_i^R)} \neq \mathbb{E}(\frac{\tilde{\beta^G}_i - \beta_i^G}{\beta_i^R}) = \mathbb{E}(\alpha_i^G)$. However, $\mathbb{E}(\tilde{\beta^G}_i - \beta_i^G) = \mathbb{E}(\beta_i^R \alpha_i^G)$ provides the average valuations of beliefs.

characteristics.[32,33] We also address the concern that the 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 percentages of average annual wages.

As shown in Figure 5, the empirical CDF reveals that in the absence of information on mentorship quality, 60% of respondents believe that female managers are worse mentors than male managers. 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 their values are very close. This would not be the case if the noise on average were not zero, even though the individual estimates could still be noisy. Similarly, in Figure 6, we observe that upon receiving information on manager quality, at least 62% of individuals prefer to work for female managers. In addition, 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 to work for female managers. Second, the amount of money that would make an individual who prefers to work for a female manager switch to a job with a male manager is higher than the amount needed to make an individual who prefers to work for a male manager switch to a job with a female manager.

7.2 Correlates of parameters with observable characteristics

In this section, we present results on how respondents' preference and belief parameters correlate with their observable characteristics. We regress each individual's estimated parameters (preference to work for male managers (β_i^G) and valuation of beliefs on male managers' mentorship skill relative to female managers' ($\beta_i^R \alpha_i^G$)) on the respondent's gen-

[32]The parameter estimates that we regress on observed demographics could be noisy, being estimated from 40 observations. This will overstate the standard errors of the regression coefficients. A finding of statistically significant estimates despite the overstated standard errors would make an even stronger case for heterogeneity.

[33]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 nonstandard since it is testing at the boundary of the parameter space—i.e., testing the null hypothesis of zero variance against the alternative hypothesis of positive variance.

der, major, family income, parental education, and parental employment. We estimate the following equations:

$$\begin{aligned}\hat{\beta}_i^G &= \gamma_0 + \gamma_1 Gender_i + \gamma_2 FamilyIncome_i + \gamma_3 Major_i + \\ &\quad \gamma_5 \mathbb{I}(\text{Mother more educated than Father})_i + \gamma_6 EmployedFather_i + \gamma_7 EmployedMother_i + \\ &\quad \gamma_8 \mathbb{I}(\text{Mother more educated than Father})_i * EmployedFather_i * EmployedMother_i + u_i\end{aligned}$$

and

$$\begin{aligned}\widehat{\beta_i^R \alpha_i^G} &= \phi_0 + \phi_1 Gender_i + \phi_2 FamilyIncome_i + \phi_3 Major_i + \\ &\quad \phi_5 \mathbb{I}(Mother\ more\ educated\ than\ Father)_i + \phi_6 EmployedFather_i + \phi_7 EmployedMother_i + \\ &\quad \phi_8 \mathbb{I}(Mother\ more\ educated\ than\ Father)_i * EmployedFather_i * EmployedMother_i + e_i\end{aligned}$$

We remove respondents whose estimated valuation of mentorship skill is either close to zero or negative. Our rationale for removing respondents with zero (or close to zero) valuations of mentorship skill comes from the identification argument. Any belief distribution can be used to rationalize responses of respondents who do not value mentorship skill, and thus, beliefs are fundamentally unidentified for such respondents. We also drop respondents whose valuation of manager mentorship ability is negative. This is because it is not clear how one can interpret a negative valuation of mentorship ability. This leads us to drop 43 such respondents and brings our sample size to 535. We present these results in Table 13. The first column has the estimates of the correlation of respondents' characteristics with their preferences for male managers and the second column the estimates of the correlation of the same set of characteristics with their valuation of beliefs on male managers' mentorship ability relative to female managers'.

We find evidence of the underlying heterogeneity in preferences and beliefs being correlated with individual education, maternal education, and parental employment. We find that respondents with a major in engineering are more likely to prefer to work for female managers than those with major in the humanities. Respondents whose mothers are weakly more educated than their fathers are less likely to have negative beliefs about female managers. Respondents with employed fathers are more likely to have negative beliefs on female manager mentorship skill. Relative to respondents whose mothers are less educated than their fathers and respondents whose both parents are unemployed, respondents with at least employed fathers (irrespective of the mother's employment status) are less likely to have negative beliefs about female manager mentorship ability. Although the focus of our paper is not on gender wage gap, we do not find evidence of differences in preferences by gender which is in contrast to recent literature focused on explaining gender wage gap with gender differences in preferences.[34] However, Mas & Pallais (2017) conclude that gender differences in preferences on work flexibility are not substantial to explain any gender gaps in wages.

The correlations of the characteristics above with the underlying heterogeneity in the distribution of beliefs on female managers point toward an important distinction between the origins of gender and race discrimination based on beliefs. Individuals who have lived in race-segregated neighborhoods have very little chance to learn about people of other races not represented in the neighborhood. However, growing up without a mother is not as common as living in a race-segregated neighborhood.[35] This argument finds support in Alesina, Ferroni & Stantcheva (2021), who find evidence that individuals who have lived in racially diverse neighborhoods tend not to hold biased beliefs on individuals of other races.

8 Robustness

8.1 Validity of belief parameter estimates

In the penultimate section of the survey, we directly elicited beliefs on manager mentorship. We did this to compare the results with those obtained from our information experiment. The objective of this exercise was not to see how close the two estimates of α^G are. As discussed earlier, the estimates of α from the model could be noisy for individuals whose β^R is close to zero. Moreover, we cannot rule out the possibility that learning could impact the estimates on beliefs obtained from the direct belief elicitation, which could thus turn out to be different from the estimates obtained from the information experiment within the job choice scenarios. The objective was instead to see whether the result on the belief in the inferiority of female managers as mentors held when beliefs were directly elicited. Although we recognize that direct elicitation of beliefs on mentorship by manager gender might induce social desirability bias, it was nevertheless a useful exercise to see to what extent the results on beliefs might be shaded from those obtained from our information experiment.

This part of the survey presented respondents with 10 jobs. Each job description ex-

[34]See Wiswall & Zafar (2018) for a detailed discussion

[35]We thank Martha Bailey for sharing this observation.

ogenously varied the manager's first name, wages and flexibility of hours. Alongside each job, we provided a zero-to-five slider scale and asked respondents to report their expected rating for each manager in each of the jobs. On these data, we project a linear model of reported expected ratings on manager gender, annual wages and flexibility of hours in alignment with the parametrization of beliefs in the job choice model.

Table 14 reports the estimates for all individuals and by respondent gender. We see that this exercise leads to the same qualitative conclusion on the belief parameter estimated from the information experiment data. We do observe that men's directly elicited beliefs are substantially lower than those elicited from the information experiment. This could arise from two sources that we cannot distinguish—shading of directly reported beliefs due to social desirability bias or learning from the scenarios that male and female managers have similar mentorship ratings. We do not observe this stark difference among female respondents. Note that these data alone can help us estimate only average beliefs α^x and not the average valuation of beliefs $\beta^r \alpha^x$ for all $x \in \{G, H, W\}$. However, the primary objective of these data is served in that they corroborate that the sign of α^G is positive in the estimates obtained both from the job choice model using the choice and compensating differential data and from the directly elicited belief data. This is an important result because it gives us additional evidence that individuals believe that women have lower average mentorship quality. Hence, any concerns about individuals manipulating their responses and misreporting their preference to work for female managers is not an issue given this corroborating evidence.

8.2 Further checks

A concern is whether individuals followed the instructions provided to them at the beginning of the survey. To evaluate this, we designed specific questions, both direct and indirect, at the end of the survey to infer whether individuals followed the instructions. We dropped the 2.2% of the sample respondents who failed these checks and reestimated the model. The estimates are robust to the use of this restricted sample.

To deal with survey inattention, we also dropped the 1% of sample respondents who finished the survey in less than 15 minutes. The choice of 15 minutes was motivated by the distribution of time completion of the survey—the 1st percentile of completion duration was at 13.89 minutes. Our estimates are robust to the imposition of this restriction as well.

9 Discussions and Implications

Given our results in the incomplete scenarios, it is important to note that an observation of indifference between male and female managers in the data should not necessarily be interpreted as evidence of no preference for one gender over the other. This can happen 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. To do so, we would need data on the population distributions of mentorship skill by manager gender. Although we are limited in this respect, we would like to highlight literature across various contexts showing consistent evidence that individuals in general 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), Bohren, Imas & Rosenberg (2019), Alesina & Stantcheva (2020), Hvidberg, Kreiner & Stantcheva (2020), Bleemer & Zafar (2018)).

It is important to discuss the interpretation of the estimates of the preferences on gender. It is hard to interpret the preferences in favor of female managers without assuming that some traits do differ systematically between males and females. Potentially the preferences we are measuring to work for females are likely associated with certain traits that are systematically different between males and females, and are valued by workers. At the end of the survey, we ask some follow-up questions on comparing male and female managers across certain traits and find that a significant share of the respondents believe that female managers are less likely to be discriminatory and more likely to be pleasant to work with, as shown in Appendix A.7 Figure A.1. At the same time it is also important to highlight that even if it were theoretically possible to make all traits identical other than biological gender, any estimate of preferences on biological gender would be hard to interpret. Similar thoughts are also expressed in Heckman (1998). This leads to philosophical questions of what does it mean to be a male or a female, if everything were equal other than their biological gender. We do not delve into the details of this specifically and focus on mentorship since it is one of the key traits that early-career workers care for in their managers.

We are measuring beliefs and preferences at a specific point in the lifecycle of workers when they are about to enter the labor market for the first time. These may not completely reflect actual choices made in the future, especially with resolution of various uncertainties and realizations of potential shocks which could matter for decision-making of the individual. Also, certain attributes may be more valuable to job-seekers when they are new in the labor market than when they are experienced. For example as individuals gain experience in the labor market it is only but natural that the valuation of mentorship would decline steadily. However, we re-emphasize that studying fresh entrants to the labor market has a few advantages. First, it is useful to study beliefs of individuals who are yet to enter the labor market because sorting into different kinds of industries and jobs can be highly driven by these beliefs (no matter whether they are biased or unbiased) and preferences. Second, among experienced workers idiosyncratic differences in work-life experiences could bias results. Hence, our results should be interpreted as measures which are representative for early career workers.

We are studying a context—elite universities in India—where the institutional setting is such that job-seekers are highly likely to be interviewed by the manager before a job is offer is made as discussed earlier. This reveals the gender of the manager before a job offer is accepted. There are many labor market contexts where this may not necessarily be the case that individuals know the gender of the manager before choosing a job. However, given our motivation that tight labor markets are one of the ideal examples where worker preferences and beliefs could matter, studying the subpopulation of individuals from elite institutions is the trade-off necessary to be made in order to understand meaningful implications of worker preferences and beliefs. Additionally, this kind of information revelation similar to our set-up is applicable in many other instances. Examples include jobseekers who have alumni networks in firms and can obtain information on managers and manager quality, thus affecting their search and consequently final match. Another example is individuals who are already employed but are seeking to switch teams within firms.

There are two primary implications of our research. First, if we fail to consider labor supply-side selection, we cannot obtain a complete picture of group-level inequalities. Additionally, studying beliefs and preferences on the supply side is essential because these affect search and equilibrium matches. As discussed in the introduction, this is particularly important in tight labor markets or markets where workers are in general harder to replace. The second implication is how firms might respond differently to such worker beliefs and preferences, which could generate different rates of promotion of women to managerial positions.[36] If firms have strong priors that matching workers with their preferred managers increases match productivity, it could potentially lead to women being promoted at higher rates, conditional on mentoring capabilities. Additionally, in tight labor markets, executives could place higher weights on workers' preferences in order to avoid high turnover costs, all else equal. However, women could still be promoted

[36] Cai & Wang (2022) show that firms and supervisors do respond to worker feedback in a firm-wide field experiment.

at lower rates if firms have sufficiently discriminatory preferences against women and are willing to forgo the increased profits resulting from more efficient matches. Thus, in a way, worker preferences could be used to test for discriminatory practices by the firm executives who decide whom to promote to managerial positions. When workers prefer to work for female managers and, conditional on productivity, women are still promoted at lower rates than men, it could be interpreted as evidence of discrimination. It would be also interesting to explore whether individuals' preferences and perceptions about average preferences differ and, more importantly, whether their perceptions are incorrect. In the spirit of Bursztyn, González & Yanagizawa-Drott (2018), incorrect perceptions of preferences could be an additional reason why female managers are promoted at lower rates.[37] Another avenue for future research is to explore whether having more female managers allows firms to profitably compete for workers with otherwise-similar firms if there is overall preference to work for female managers. Additionally, if there are information asymmetries between incumbent and competing firms (Pinkston (2009), Kahn (2013)), then there are even higher information rents to be taken advantage of.

10 Conclusion

In this paper, we document how does manager's gender and ability influences workers' job choice. We provide novel evidence on the distribution of workers' preferences on manager gender and their beliefs on managers' mentoring ability. To do so, we designed and conducted a hypothetical job choice survey involving an information experiment among job seeking students at a highly selective university in India. We presented respondents with a series of hypothetical job scenarios consisting of jobs with exogenously varying attributes (annual wages, flexibility of hours, and manager name and mentorship rating). Respondents were asked to choose their most preferred job and report the wage compensating differentials that would make them indifferent between jobs. We embed a within-individual information experiment wherein manager mentorship rating were only shown in the last ten (complete) scenarios, but were not shown in the first ten (incomplete) scenarios. 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 skill. We not only show identification using compensat-

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

ing differentials, but also show that choice probabilities cannot identify the distribution of the belief parameters. We find that in the absence of information on manager mentorship, where their choices are driven by both preferences and beliefs, workers are indifferent between male and female managers. However, in the presence of information on manager mentorship skill, we find a strong preference to work for female managers. We estimate a structural model of job choice, and find that individuals are willing to forgo on average 1.7% of average annual wages to work for female managers. Hence, in the absence of additional information on manager mentorship ability, female managers are believed to be worse mentors than male managers. We quantify these negative beliefs against female managers at approximately 1.6% of average annual wages. We corroborate these results on negative beliefs on female manager mentorship using additional data on directly elicited beliefs. Importantly, we uncover rich heterogeneity in the underlying distributions of individuals' preferences and beliefs. Estimating the model for each worker, we find that preferences and beliefs correlate with demographics in the expected directions. In particular, we do not find evidence of negative beliefs on female manager mentorship ability among those whose mothers are more educated than their fathers, and stronger preference to work for female managers among individuals majoring in engineering than those majoring in humanities. As discussed in detail in the previous section, our results suggest that estimates of discrimination by firm executives in generating a glass ceiling for women at managerial levels could be downward biased if, conditional on quality, women are still promoted at lower rates. To the extent that this is the case, especially in tight markets, our paper sheds light on how additional data on worker preferences and beliefs on manager characteristics could be used to indirectly test for discrimination among the firm executives who decide on promotions.

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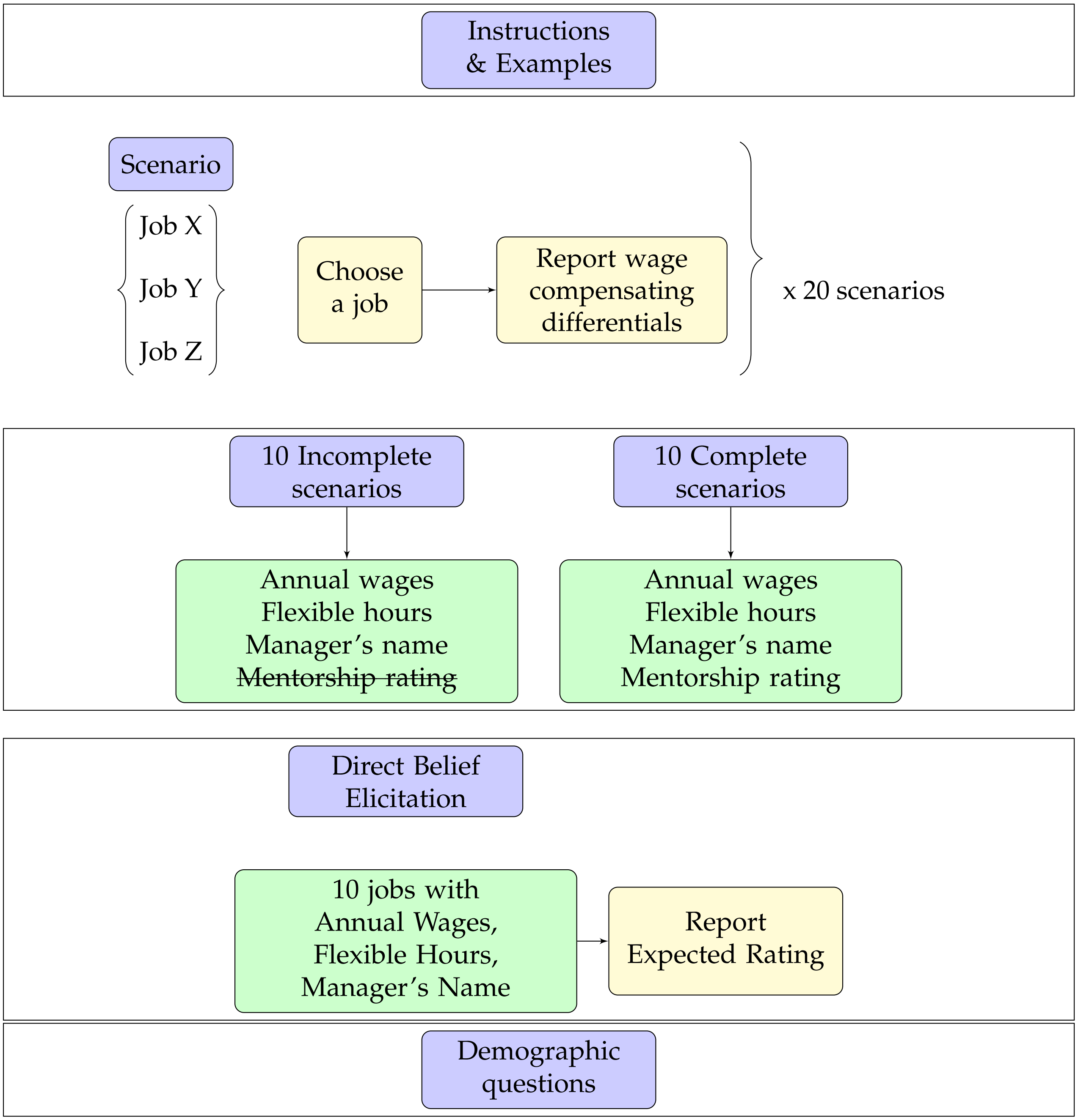
Tables and Figures

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 do not choose, individuals are asked to report the minimum increase in wages that they would need to choose those jobs instead. There are 20 such scenarios. In the first 10 scenarios, individuals do not observe the manager mentorship rating; however, in the last 10, they do, 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: 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

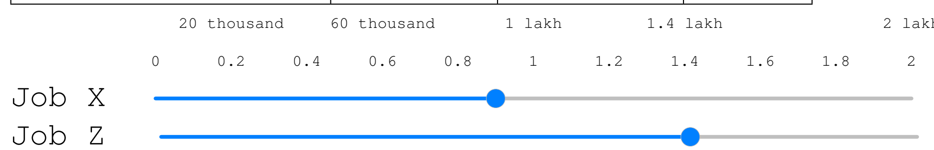
Job Y

Job Z

Compensating differential (*if job chosen was Y*)

You chose Job Y.
If you were to negotiate your wage, how much of a 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: Jobs X and Z have male managers and Job Y has a female manager. Across the 10 incomplete scenarios, five scenarios have two jobs with male managers and one job with a female manager, and the remaining five have two jobs with female managers and one job with a male manager.

Table 2: 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

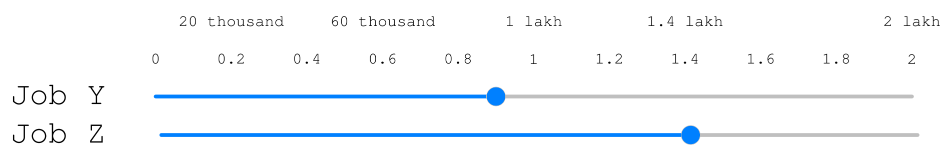
Job Y

Job Z

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

You chose Job X.
If you were to negotiate your wage, how much of a 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: Jobs X and Y have male managers, and Job Z has a female manager. Overall, across the 10 complete scenarios, five scenarios have two jobs with male managers and one job with a female manager, and the remaining five have two jobs with female managers and one job with a male manager.

Table 3: 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

Notes: This table shows the summary statistics of job attributes (annual wages and flexible hours) in the 60 jobs shown to respondents (3 jobs per scenario across 10 incomplete and 10 complete scenarios). The mentorship rating summary statistics comes from the last 30 jobs because they are only shown in the last 10 complete scenarios with 3 jobs each.

Table 4: Job attributes across male and female managers

Attribute	Male Manager	Female Manager	Difference	p-value
Rating	3.373	3.447	0.073	0.692
(only complete scenarios)	(0.519)	(0.485)		
	[0.134]	[0.125]	[0.183]	
Flexible hours	0.567	0.500	-0.067	0.612
	(0.504)	(0.509)		
	[0.092]	[0.093]	[0.131]	
Annual wages	7.080	7.140	0.060	0.876
	(1.529)	(1.445)		
	[0.279]	[0.264]	[0.384]	

Notes: This table shows the summary statistics of job attributes (annual wages and flexible hours) by the gender of the manager in the 60 jobs shown to respondents (3 jobs per scenario across 10 complete and 10 incomplete scenarios) and the mentorship rating summary statistics by the gender of the manager comes from the last 30 jobs because they are only shown in the last 10 complete scenarios with 3 jobs each. Numbers in parentheses contain standard deviations and numbers in square brackets contain standard errors.

Table 5: Job attributes across male and female managers by complete and incomplete scenarios

Panel A: Incomplete scenarios

Attribute	Male Manager	Female Manager	Difference	p-value
Flexible hours	0.6	0.533	-0.067	0.724
	(0.507)	(0.516)		
	[0.131]	[0.133]	[0.187]	
Annual wages	7.373	7.127	-0.247	0.661
	(1.533)	(1.518)		
	[0.396]	[0.392]	[0.557]	

Panel B: Complete scenarios

Attribute	Male Manager	Female Manager	Difference	p-value
Flexible hours	0.467	0.533	0.067	0.726
	(0.516)	(0.516)		
	[0.133]	[0.133]	[0.189]	
Annual wages	6.787	7.153	0.367	0.501
	(1.520)	(1.423)		
	[0.392]	[0.367]	[0.538]	
Rating	3.373	3.447	0.073	0.692
	(0.519)	(0.485)		
	[0.134]	[0.125]	[0.183]	

Notes: This table shows the summary statistics of job attributes (annual wages and flexible hours) by the gender of the manager separately in the incomplete and in the complete scenarios. The mentorship rating summary statistics by the gender of the manager comes from the last 30 jobs because they are only shown in the last 10 complete scenarios with 3 jobs each. Numbers in parentheses contain standard deviations and numbers in square brackets contain standard errors. Numbers in parentheses contain standard deviations and numbers in square brackets contain standard errors.

Table 6: 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	37.6	24.4	32.1
(Less than $9,492)			
2 lakhs to 5 lakhs	26.9	24.0	25.7
($9,492 to $23,730)			
5 lakhs to 10 lakhs	21.3	30.2	25.0
($23,730 to $47,460)			
10 to 20 lakhs	11.5	15.3	13.1
($47,460 to $94,921)			
Above 20 lakhs	2.7	6.2	4.1
(Above $94,921)			
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
Homemaker	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
Homemaker	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 a deceased parent. Variables on income categories are in INR and have their corresponding purchasing power parity–adjusted USD equivalent below each category.

Table 7: Percentages of chosen jobs with male and female managers, by scenario

Respondent	*All*		*Female*		*Male*	
Manager / *Scenario*	**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

Notes: The table shows the percent of jobs chosen with male and female managers in the incomplete scenarios (where mentorship rating was not shown the respondents) and in the complete scenarios (where mentorship rating was shown). Percentages are shown for all respondents and disaggregated by the respondent's gender.

Table 8: Average compensating differentials for unchosen jobs, by manager gender 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)	

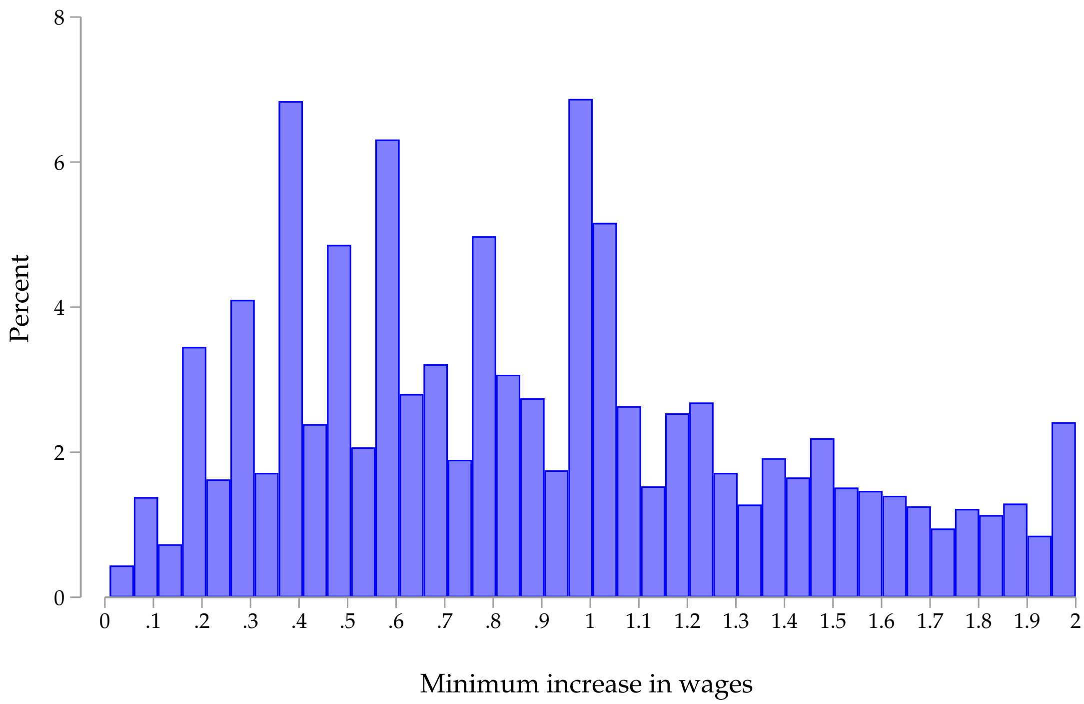
Notes: Units are in 1 lakh (hundred thousand) INR. The table shows the average compensating differentials demanded by respondents in unchosen jobs with male and female managers in the incomplete scenarios (where mentorship rating was not shown the respondents) and in the complete scenarios (where mentorship rating was shown). Numbers are shown for all respondents and disaggregated by the respondent's gender.

Table 9: 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)
Scenario FE	yes
Observations	17,400

Notes: The estimates show the marginal effects of each of the attributes in the difference-in-differences specification (1). Standard errors bootstrapped at the individual level with 1,000 replications. The total number of observations is 17,400 because we use individual-level choice data on 3 jobs in each of the 10 complete scenarios for 580 individuals.

Figure 4: Reported compensating differentials in unchosen jobs



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

Table 10: Complete and incomplete scenarios: Jointly estimated

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

Notes: The table shows estimates from estimating equation system (16) for each individual and reports the averages $\mathbb{E}(\tilde{\beta}_i^x)$ for each attribute $x \in \{G, H, W\}$ in the incomplete scenarios and $\mathbb{E}(\beta_i^x)$ for each attribute $x \in \{G, H, R\}$ in the complete scenarios. β_i^W is normalized to 1. Estimates are represented in two sets of units—the first is in hundred thousand INR, and the second converts those units into percentages of average annual wages. Standard errors are computed using the the block bootstrap at the individual level with 1,000 replications. Statistical significance at 1, 5, and 10% is denoted by ***, **, and *, respectively.

Table 11: Estimates of belief parameters

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

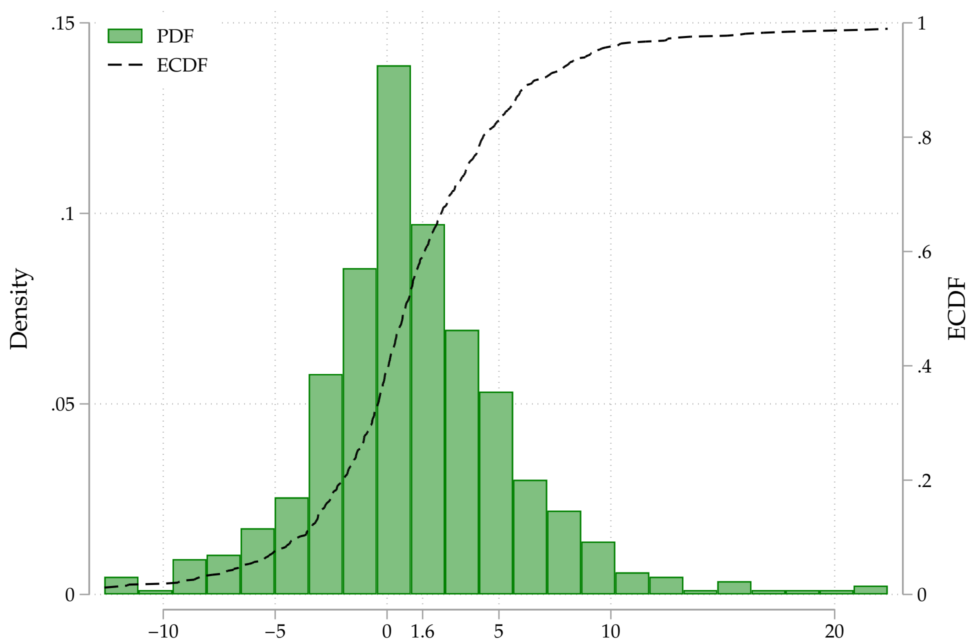
Notes: Standard errors are computed using the block bootstrap at the individual level with 1,000 repetitions. Parameters are estimated by jointly estimating the complete and incomplete scenarios and using the estimates of β^R $\tilde{\beta}^G$ and β^G presented in Table 10. The estimates come from the equation $\alpha_i^G = \frac{\tilde{\beta}_i^G - \beta_i^G}{\beta_i^R}$. Statistical significance at 1, 5, and 10% is denoted by ***, **, and *, respectively.

Table 12: Estimates of valuation of beliefs on male relative to female manager mentorship ability

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

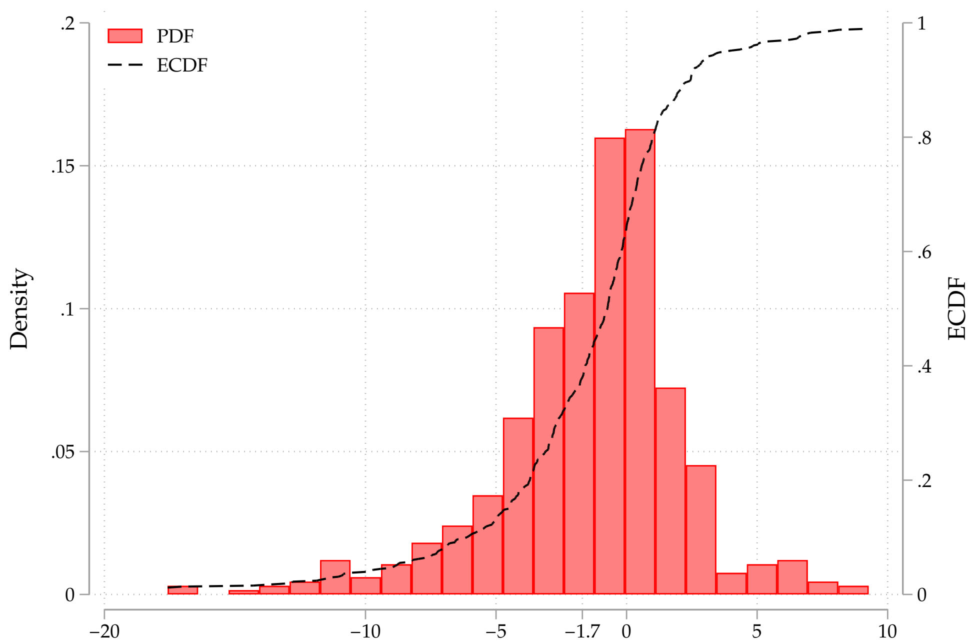
Notes: The table shows the average of individual estimates of the valuation of beliefs on male manager mentorship. This comes from the equation $\beta_i^R \alpha_i^G = \tilde{\beta}_i^G - \beta_i^G$ for all $x \in \{G, W, H\}$ presented in Table 10. The standard errors are block bootstrapped at the individual level with 1,000 repetitions. Parameters are estimated by jointly estimating the complete and incomplete scenarios. Statistical significance at 1, 5, and 10% is denoted by ***, **, and *, respectively. Average annual wages equal 7 lakh INR ($\approx$ \$38.8 thousand in PPP).

Figure 5: Distribution of valuation of individual beliefs as a percentage of average annual wages



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 unit on the x-axis is the percentage of average annual wages.

Figure 6: Distribution of valuation of individual preferences as a percentage of average annual wages



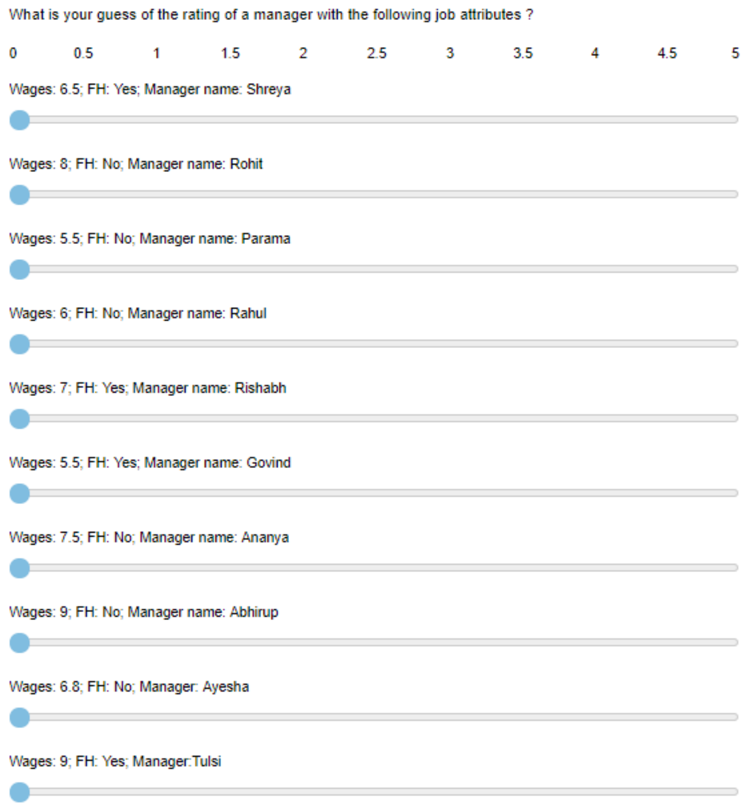
Notes: The figure plots the histogram and the smoothed empirical cumulative distribution function of individual preferences obtained by estimating the model for each individual. The unit on the x-axis is the percentage of average annual wages.

Table 13: Correlations of estimated parameters with individual characteristics

	Preferences	Valuation of beliefs
Female	-0.000	-0.010
	(0.023)	(0.037)
Major		
Engineering	-0.063**	0.044
	(0.032)	(0.052)
Science	-0.039	0.023
	(0.027)	(0.042)
Education		
Masters	-0.018	0.052
	(0.029)	(0.048)
MPhil/PhD	0.052	-0.045
	(0.080)	(0.124)
Family income		
2 to 5 lakhs ($9,492 to $23,730)	0.009	-0.010
	(0.027)	(0.043)
5 to 10 lakhs ($23,730 to $47,460)	-0.002	-0.027
	(0.028)	(0.045)
10 to 20 lakhs ($47,460 to $94,921)	0.008	0.014
	(0.034)	(0.054)
Above 20 lakhs (Above $94,921)	-0.035	0.040
	(0.054)	(0.090)
1(Mother education $\geq$ father education)	0.007	-0.194**
	(0.060)	(0.093)
1(Father employed)	-0.049	0.198***
	(0.041)	(0.065)
1(Mother employed)	0.019	-0.002
	(0.030)	(0.049)
Mother more educated than father $\times$ Father employed $\times$ Mother employed		
NNY	0.041	-0.170
	(0.093)	(0.144)
NYN	0.039	-0.218**
	(0.065)	(0.102)
NYY	0.041	-0.273**
	(0.075)	(0.119)
YNY	-0.043	0.088
	(0.069)	(0.111)
Observations	578	535
R^2	0.01	0.01

Notes: Error terms in both regressions are homoskedastic. This is because the underlying identification of the preference and belief parameters is within-individual, which leads to the error terms being i.i.d.

Figure 7: Expected rating



What is your guess of the rating of a manager with the following job attributes ?

0 0.5 1 1.5 2 2.5 3 3.5 4 4.5 5

Wages: 6.5; FH: Yes; Manager name: Shreya

Wages: 8; FH: No; Manager name: Rohit

Wages: 5.5; FH: No; Manager name: Parama

Wages: 6; FH: No; Manager name: Rahul

Wages: 7; FH: Yes; Manager name: Rishabh

Wages: 5.5; FH: Yes; Manager name: Govind

Wages: 7.5; FH: No; Manager name: Ananya

Wages: 9; FH: No; Manager name: Abhirup

Wages: 6.8; FH: No; Manager: Ayesha

Wages: 9; FH: Yes; Manager:Tulsi

Table 14: Estimates of expected beliefs from directly elicited belief data

	Model			Data on beliefs		
Belief Parameters	All	Women	Men	All	Women	Men
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 1,000 repetitions. These estimates in the right panel of "Data on beliefs" come from projecting a linear model on the data of the reported expected manager rating in each of 10 different jobs with annual wages, flexibility of hours and manager 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 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 first show the identification of preferences when information is complete in Step 1. Then, with incomplete information in Step 2, we 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,

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

A compensating differential of Δ_{ijk} makes i indifferent between jobs j and k when i observes X_j and X_k. Hence, given that a compensating differential increases only wages and changes nothing else about the job, we have $\mathbb{E}_i[\epsilon_{ik} \mid X_k, \Delta_{ijk}] = \mathbb{E}_i[\epsilon_{ik} \mid X_k]$. Normalizing the preference parameter on wages to 1, we have

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

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

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

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

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

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 $G_i(R \mid \tilde{X})$. Now, we have

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

The expectation here varies by individuals. This allows different individuals to draw from different distributions of mentorship, which may not necessarily be the true distribution. 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 increases only wages and changes nothing else about the job, and normalizing the preference parameter on wages to 1, we have

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

Given that everything else about the job is assumed to be the same, we have $\mathbb{E}_i[\epsilon_{ik} \mid \widetilde{X_k}] = \mathbb{E}_i[\epsilon_{ij} \mid \widetilde{X_j}]$ for all jobs $j \neq k$.
Since by definition $\widetilde{\Delta_{ijk}} = \mathbb{E}_i[U_{ij} \mid \widetilde{X_j}] - \mathbb{E}_i[U_{ik} \mid \widetilde{X_k}, \widetilde{\Delta_{ijk}}]$, we have

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

Note that this integration is over the belief distribution of the individual about the mentorship quality of potential managers. Assuming that moments exist, as the number of scenarios go to infinity, the above identifies individual i's belief distribution $G_i(R \mid \widetilde{X})$, 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 approaches infinity.

Note that beliefs $G_i(R \mid \widetilde{X})$ are not identified under two circumstances. First, if i does not care about R, then the choices made and the compensations reported are not driven by whatever way i may expect R to vary with $\widetilde{X}$. To see this mathematically, if i does not care about R, then the above set of equations become independent of $G_i(R \mid \widetilde{X})$ because $\mathbb{E}_i[u_i(X_j) \mid \widetilde{X_j}] = \mathbb{E}_i[u_i(\widetilde{X_j}) \mid \widetilde{X_j}] = u_i(\widetilde{X_j})$. The first equality follows from $\widetilde{X_j} \equiv X_j \setminus R_j$, and i does not care about R. Second, if R is independent of $\widetilde{X}$, then no variation in $\widetilde{X}$ can generate any variation in the beliefs and thus will not be reflected in the choices and compensating differentials. To see this mathematically, if R is independent of $\widetilde{X}$, then $G_i(R \mid \widetilde{X}) = G_i(R)$. This makes $\mathbb{E}_i[u_i(X_j) \mid \widetilde{X_j}] \equiv \mathbb{E}_i[u_i(\widetilde{X_j}, R_j) \mid \widetilde{X_j}]$ a function that is independent of R_j by the law of iterated expectations.

A.2 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 incomplete scenarios. In particular, we estimate the following constrained least squares regression with no constant:

$$\begin{bmatrix} \mathbf{\Delta_{jk}} \\ \vdots \\ \widetilde{\mathbf{\Delta}}_{\mathbf{jk}} \\ \vdots \end{bmatrix} = \begin{bmatrix} \mathbf{X_j} - \mathbf{X_k} & \mathbf{0} \\ \vdots & \vdots \\ \mathbf{0} & \widetilde{\mathbf{X}}_{\mathbf{j}} - \widetilde{\mathbf{X}}_{\mathbf{k}} \\ \vdots & \vdots \end{bmatrix}' (\boldsymbol{\beta} \quad \widetilde{\boldsymbol{\beta}}) + \mathbf{e} \tag{18}$$

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 bootstrap at the student level. This accounts for any arbitrary correlation between responses at the student level.

The block bootstrap algorithm is as follows: The 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 the mean and standard deviation of the B estimates in hand to generate estimates of the bootstrap mean and bootstrap standard error.

Preferences:

$$\begin{aligned} \hat{\mathbb{E}}(\beta_i) &= \frac{1}{B}\sum_{b=1}^{B} \hat{\beta}^{(b)} \\ \widehat{\text{std error}}(\beta_i) &= SD(\hat{\beta}^{(b)}) \end{aligned}$$

Preferences confounded with valuation of beliefs:

$$\begin{aligned} \hat{\mathbb{E}}(\tilde{\beta}_i) &= \frac{1}{B}\sum_{b=1}^{B} \hat{\tilde{\beta}}^{(b)} \\ \widehat{\text{std error}}(\tilde{\beta}_i) &= SD(\hat{\tilde{\beta}}^{(b)}) \end{aligned}$$

Valuation of beliefs:

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

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

Figure 8: Bootstrap distribution of beliefs on male managers' mentorship and preferences to work for male managers

Notes: The figure shows bootstrap distributions of beliefs on male manager mentorship and preferences to work for male managers, relative to female managers in the percentage of average annual wages. The bootstrap distributions are obtained from 1,000 block bootstrapped samples, using the algorithm described in Appendix A.2. These bootstrap distributions are used for estimation of means and standard errors of preferences and beliefs.

A.3 Alternate models

In this section, we illustrate some examples by relaxing the linearly separable model to include interactions. These models are identified as shown in the Appendix above.

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

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

In the complete scenarios individuals observe $X_j \equiv \{G_j, W_j, H_j, R_j\}$ and in the incomplete scenarios individuals observe $\widetilde{X_j} \equiv X_j \setminus \{R_j\}$. We specify the belief function of individual i as $\mathbb{E}_i(R_j \mid \widetilde{X_j}) = \widetilde{X}_j' \alpha_i$

Throughout this section, we maintain the same assumptions parallel to our instructions:

Assumption (1): All attributes not mentioned in the survey are the same for all jobs.

Assumption (2): The reported compensating differential increases only wages and changes nothing else about the job.

A.3.1 Model with an interaction of manager gender (G) and manager mentorship rating (R)

In this example, the utility of individual i is given by

$$U_{ij} = \sum_{x \in X} \beta_i^x x_j + \beta_i^{GR} G_j R_j + \epsilon_{ij}$$

Thus, the parameter space now contains 5 preference parameters:

$$\beta_i \equiv \{\beta_i^G, \beta_i^H, \beta_i^W, \beta_i^R, \beta_i^{GR}\}$$

and 4 belief parameters:

$$\alpha_i \equiv \{\alpha_i^G, \alpha_i^H, \alpha_i^W\}$$

Complete scenarios

In the complete scenarios, we have for all i

$$\mathbb{E}_i[U_{ij} \mid X_j] = \sum_{x \in X} \beta_i^x x_j + \beta_i^{GR} G_j R_j + \mathbb{E}_i(\epsilon_{ij} \mid X_j)$$

In any other job k that is not chosen, supposing that the individual reports Δ_{ijk} as the compensating differential, we have

$$\mathbb{E}_i[U_{ik} \mid X_k, \Delta_{ijk}] = \sum_{x \in X} \beta_i^x x_k + \beta_i^{GR} G_k R_k + \beta_i^W \Delta_{ijk} + \mathbb{E}_i(\epsilon_{ik} \mid X_k, \Delta_{ijk})$$

Given assumption (2), we have $\mathbb{E}_i(\epsilon_{ik} \mid X_k, \Delta_{ijk}) = \mathbb{E}_i(\epsilon_{ik} \mid X_k)$, which by assumption (1) is equal to $\mathbb{E}_i(\epsilon_{ij} \mid X_j)$.

Thus, normalizing $\beta_i^W = 1$, we have,

$$\Delta_{ijk} = \sum_{x \in X} \beta_i^x (x_j - x_k) + \beta_i^{GR} (G_j R_j - G_k R_k) \tag{19}$$

Incomplete scenarios

In the incomplete scenarios, we have

$$\mathbb{E}_i[U_{ij} \mid \widetilde{X}_j] = \sum_{x \in \widetilde{X}} \beta_i^x x_j + \mathbb{E}_i(\beta_i^R R_j + \beta_i^{GR} G_j R_j + \epsilon_{ij} \mid \widetilde{X}_j)$$

Assuming as before that individuals know their preference parameters, this simplifies to

$$\mathbb{E}_i[U_{ij} \mid \widetilde{X}_j] = \sum_{x \in \widetilde{X}} \beta_i^x x_j + \beta_i^R \mathbb{E}_i(R_j \mid \widetilde{X}_j) + \beta_i^{GR} G_j \mathbb{E}_i(R_j \mid \widetilde{X}_j) + \mathbb{E}_i(\epsilon_{ij} \mid \widetilde{X}_j)$$

Using the belief function specified above, we have,

$$\mathbb{E}_i[U_{ij} \mid \widetilde{X}_j] = \sum_{x \in \widetilde{X}} (\beta_i^x + \beta_i^R \alpha_i^x) x_j + \beta_i^{GR} G_j \sum_{x \in \widetilde{X}} \alpha_i^x x_j + \mathbb{E}_i(\epsilon_{ij} \mid \widetilde{X}_j)$$

In any other job k that is not chosen, supposing that the individual reports $\widetilde{\Delta}_{ijk}$ as the compensating differential, we have

$$\begin{aligned} \mathbb{E}_i[U_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}] \quad &= \quad \sum_{x \in \widetilde{X}} (\beta_i^x + \beta_i^R \alpha_i^x) x_k + \beta_i^{GR} G_k \sum_{x \in \widetilde{X}} \alpha_i^x x_k + \beta_i^W \widetilde{\Delta}_{ijk} \\ &+ \quad \mathbb{E}_i(\epsilon_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) \end{aligned}$$

Given assumption (2), we have $\mathbb{E}_i(\epsilon_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) = \mathbb{E}_i(\epsilon_{ik} \mid \widetilde{X}_k)$, which by assumption (1) is equal to $\mathbb{E}_i(\epsilon_{ij} \mid \widetilde{X}_j)$.

Normalizing $\beta_i^W = 1$, we have

$$\widetilde{\Delta}_{ijk} = \sum_{x \in \widetilde{X}} \left(\beta_i^x + \beta_i^R \alpha_i^x\right)(x_j - x_k) + \beta_i^{GR}\left(G_j \sum_{x \in \widetilde{X}} \alpha_i^x x_j - G_k \sum_{x \in \widetilde{X}} \alpha_i^x x_k\right)$$

which simplifies to

$$\widetilde{\Delta}_{ijk} = \sum_{x \in \widetilde{X}} \left(\beta_i^x + \beta_i^R \alpha_i^x\right)(x_j - x_k) + \beta_i^{GR} \sum_{x \in \widetilde{X}} \alpha_i^x \left(x_j G_j - x_k G_k\right) \tag{20}$$

An important difference to note in this model relative to the linearly separable model is that β_i^G alone no longer captures how much worker i values a male manager over a female manager. In this case, it is

$$U_{ij} \mid_{G_j=1} - U_{ij} \mid_{G_j=0} = \beta_i^G + \beta_i^{GR} R_j$$

Thus, the average valuation of a male manager by worker i is $\beta_i^G + \beta_i^{GR} \mathbb{E}_i(R_j)$.[38]

The valuation of beliefs is also different from that in the linearly separable model. This is because it is no longer weighted only by how much individuals care about mentorship quality (β_i^R) and now is augmented by how much individuals care about mentorship quality by manager gender. Using the equations above, we can show that the valuation of beliefs on mentorship for male managers relative to its counterpart for female managers in this model is

$$\alpha_i^G(\beta_i^R + \beta_i^{GR})$$

The incomplete scenarios identify $\beta_i^G + \alpha_i^G(\beta_i^R + \beta_i^{GR})$, $\beta_i^H + \beta_i^R \alpha_i^H$, $\beta_i^W + \beta_i^R \alpha_i^W$ and $\{\alpha_i^x \beta_i^{GR}\}_{x \in \{H,W\}}$. Given that the complete scenarios identify $\{\beta_i^x\}_{x \in X}$ and β_i^{GR}, the incomplete scenarios identify $\{\alpha_i^x\}_{x \in \widetilde{X}}$.[39]

[38]The expectation does not condition on manager gender because the attributes are exogenously provided to the respondents and thus the mentorship rating does not significantly differ between male and female managers.

[39]Similarly, if one were to use an interaction of the mentorship rating (R) with flexible hours (H), the corresponding complete scenario equation would be

$$\Delta_{ijk} = \sum_{x \in X} \beta_i^x (x_j - x_k) + \beta_i^{HR}(H_j R_j - H_k R_k)$$

, and the incomplete scenario equation would be

$$\widetilde{\Delta}_{ijk} = \sum_{x \in \widetilde{X}} \left(\beta_i^x + \beta_i^R \alpha_i^x\right)(x_j - x_k) + \sum_{x \in \widetilde{X}} \alpha_i^x \beta_i^{HR} \left(x_j H_j - x_k H_k\right)$$

.

A.3.2 Model with interaction of (G) and (H) in the beliefs for rating

We specify the belief function now as

$$\mathbb{E}_i(R_j \mid \widetilde{X_j}) = \sum_{x \in \widetilde{X}} \alpha_i^x x_j + \alpha_i^{GW} G_j H_j$$

The utility function is unchanged at

$$U_{ij} = \sum_{x \in X} \beta_i^x x_j + \epsilon_{ij}$$

From the complete scenarios, following similar steps, we can derive

$$\Delta_{ijk} = \sum_{x \in X} \beta_i^x (x_j - x_k) \tag{21}$$

From the incomplete scenarios, following similar steps, we can derive

$$\widetilde{\Delta}_{ijk} = \sum_{x \in \widetilde{X}} \left(\beta_i^x + \beta_i^R \alpha_i^x\right)(x_j - x_k) + \beta_i^R \alpha_i^{GW} \left(G_j H_j - G_k H_k\right) \tag{22}$$

Following similar arguments, we can show that all parameters in this model are identified.

In this model, the valuation of a male manager relative to that of a female manager by worker i is given as β_i^G. However, the valuation of beliefs will no longer be $\beta_i^R \alpha_i^G$. The valuation of beliefs of worker i on male managers' mentorship ability relative to female managers' mentorship ability in job j is

$$\begin{aligned}
&\beta_i^R \left[\mathbb{E}_i(R_j \mid G_j = 1, W_j, H_j) - \mathbb{E}_i(R_j \mid G_j = 0, W_j, H_j)\right] \\
&= \beta_i^R \left[\alpha_i^G + \alpha_i^{GW} H_j\right]
\end{aligned}$$

The valuation of the corresponding beliefs by worker i is $\beta_i^R \left[\alpha_i^G + \alpha_i^{GW} \mathbb{E}(H_j)\right]$. Note that here the expectation does not vary by individuals because they observe H_j and it serves as an observable average that individuals take over jobs. Given the distribution of H_j and the identified preference and belief parameters for each worker i, the above equation identifies the distribution of the valuation of beliefs on male managers' mentorship rating relative to female managers'.

A.3.3 Model with log(wages)

In this model, the only minor difference is in the estimating equations since now the compensating differential is not separable from the wages due to the nonlinear logarithmic function. We keep other parts of the model linearly separable for simplicity; however, they can be relaxed as shown in the previous subsections.

$$U_{ij} = \beta_i^G G_j + \beta_i^H H_j + \beta_i^W log(w_j) + \beta_i^R R_j + \epsilon_{ij}$$

Thus, the parameter space now contains 4 preference parameters:

$$\beta_i \equiv \{\beta_i^G, \beta_i^H, \beta_i^R\}$$

with β_i^W normalized to 1, and 4 belief parameters:

$$\alpha_i \equiv \{\alpha_i^G, \alpha_i^H, \alpha_i^W\}$$

Complete scenarios

In the complete scenarios, we have for all i

$$\mathbb{E}_i[U_{ij} \mid X_j] = \beta_i^G G_j + \beta_i^H H_j + \beta_i^W log(w_j) + \beta_i^R R_j + \mathbb{E}_i(\epsilon_{ij} \mid X_j)$$

In any other job k that is not chosen, supposing that the individual reports Δ_{ijk} as the compensating differential, we have

$$\mathbb{E}_i[U_{ik} \mid X_k, \Delta_{ijk}] = \beta_i^G G_k + \beta_i^H H_k + \beta_i^W log(w_k + \Delta_{ijk}) + \beta_i^R R_k + \mathbb{E}_i(\epsilon_{ik} \mid X_k, \Delta_{ijk})$$

Given assumption (2), we have $\mathbb{E}_i(\epsilon_{ik} \mid X_k, \Delta_{ijk}) = \mathbb{E}_i(\epsilon_{ik} \mid X_k)$, which by assumption (1) is equal to $\mathbb{E}_i(\epsilon_{ij} \mid X_j)$.

Thus, normalizing $\beta_i^W = 1$, we have

$$\frac{log(w_k + \Delta_{ijk})}{log(w_j)} = \beta_i^G (G_j - G_k) + \beta_i^H (H_j - H_k) + \beta_i^R (R_j - R_k) \tag{23}$$

This identifies $\{\beta_i^G, \beta_i^H, \beta_i^R\}$ for each individual i. In this model, the valuation of preferences to work for a male manager relative to that of a female manager by worker i is given as β_i^G.

Incomplete scenarios

In the incomplete scenarios, we have

$$\mathbb{E}_i[U_{ij} \mid \widetilde{X_j}] = \beta_i^G G_j + \beta_i^H H_j + \beta_i^W log(w_j) + \beta^R \mathbb{E}_i(R_j \mid \widetilde{X}_j) + \mathbb{E}_i(\epsilon_{ij} \mid \widetilde{X}_j)$$

For job k and compensating differential $\widetilde{\Delta}_{ijk}$, we have

$$\mathbb{E}_i[U_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}] = \beta_i^G G_k + \beta_i^H H_k + \beta_i^W log(w_k + \widetilde{\Delta}_{ijk}) + \beta^R \mathbb{E}_i(R_k \mid \widetilde{X}_j, \widetilde{\Delta}_{ijk}) + \mathbb{E}_i(\epsilon_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk})$$

or,

$$\mathbb{E}_i[U_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}] = \beta_i^G G_k + \beta_i^H H_k + \beta_i^W log(w_k + \widetilde{\Delta}_{ijk}) + \beta^R \mathbb{E}_i(R_k \mid \widetilde{X}_j) + \mathbb{E}_i(\epsilon_{ik} \mid \widetilde{X}_k)$$

This stems from the assumption that the compensating differential does not change anything about the job except for the wages. Hence, this will not change the expected rating. That is,

$$\begin{aligned} \mathbb{E}(R_k \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) &= \mathbb{E}(R_k \mid \widetilde{X}_k) \\ &= \alpha_i^G G_k + \alpha_i^H H_k + \alpha_i^W log(w_k) \end{aligned}$$

Simplifying expected utility of individual i for job k and compensating differential $\widetilde{\Delta}_{ijk}$ with respect to job j, we have

$$\mathbb{E}_i[U_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}] = (\beta_i^G + \beta_i^R \alpha_i^G) G_k + (\beta_i^H + \beta_i^R \alpha_i^H) H_k + \beta_i^W log(w_k + \widetilde{\Delta}_{ijk}) + \beta_i^R \alpha_i^W log(w_k) + \mathbb{E}_i(\epsilon_{ij} \mid \widetilde{X}_j)$$

Using arguments as above, and normalizing $\beta_i^W = 1$, we have

$$\frac{log(w_k + \widetilde{\Delta}_{ijk})}{log(w_j)} = (\beta_i^G + \beta_i^R \alpha_i^G)(G_j - G_k) + (\beta_i^H + \beta_i^R \alpha_i^H)(H_j - H_k) + \beta_i^R \alpha_i^W \left(log(w_j) - log(w_k)\right) \tag{24}$$

This identifies $\{\beta_i^G + \beta_i^R \alpha_i^G, \beta_i^H + \beta_i^R \alpha_i^H, \beta_i^R \alpha_i^W\}$ for each individual i. Thus valuation of beliefs on male manager mentorship which is given as $\beta_i^R \alpha_i^G$ is identified from the variation between the complete and the incomplete scenarios.

A.4 Model with scaled mentorship rating $f(R_j)$

In this sub-section we explore identification when we allow utility over mentorship, R to be linear in $\beta_i^R f(R_j)$ for a monotone increasing $f(.)$ instead of being linear in $\beta_i^R R_j$.[40]

Indeed, since individuals hold $f(.)$ fixed while reporting their choices and compensating differentials, our exogenous variations in the survey cannot non-parametrically identify $f(.)$. This is true even if $f(.)$ does not vary by individuals. However, for any given $f()$, we show that the preference and belief parameters are non-parametrically identified.

To see identification, define $X_j \equiv \left\{G_j, W_j, H_j, f(R_j)\right\}$. Each individual $i \in \{1, ..., N\}$ has preferences on attributes X_j in job $j \in \{1, ..., J\}$ given by

$$U_{ij} = \sum_{x \in X} \beta_i^x x_j + \epsilon_{ij}$$

In the incomplete scenarios, where individuals do not observe R_j, we now specify the belief function of individual i as $\mathbb{E}_i\left[f(R_j) \mid \widetilde{X_j}\right] = \widetilde{X}_j'\alpha_i$ where $\widetilde{X_j} \equiv X_j \setminus \{f(R_j)\}$. Given this the proof of identification of the parameters follows identical steps to the baseline case discussed in the main text and shown in Appendix A.1.

Hence, the intuition of identification remaining the same as before, the additional modification which facilitates identification in this set-up is to specify the belief function as $\mathbb{E}_i\left[f(R_j) \mid \widetilde{X_j}\right]$ for any given $f(.)$ instead of $\mathbb{E}_i\left[R_j \mid \widetilde{X_j}\right]$. Additionally, note that in allowing preferences on mentorship to be linear in $\beta_i^R f(R_j)$ for a monotone increasing $f(.)$, even though the parameters of the model are identified, the interpretation of the parameters change. In particular, the preference parameter β_i^R tells us the willingness to forgo wages for a unit increase in $f(R_j)$ instead of a unit increase in R_j. This interpretation is parallel to the argument of non-identification of $f()$. If $f()$ were identified, we could have identified the willingness to forgo wages for a unit increase in R_j. To see this observe that, if $f()$ were identified, then $\frac{\partial f(R_j)}{\partial R_j}$ is identified, and hence the willingness to forgo wages for a unit increase in R_j i.e., $\beta_i^R \frac{\partial f(R_j)}{\partial R_j}$ would have been identified.

[40] We thank an anonymous referee for suggesting us to explore this.

A.5 Model with mentorship quality as a proxy for overall manager quality

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 manager mentorship ability. In this specification, individuals care about overall manager quality (Q) in addition to caring about wages, flexibility of hours and manager gender. 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 finding of belief-based 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:

$$U_{ij} = \sum_{x \in A} \beta_i^x x_j + \epsilon_{ij} \tag{25}$$

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

$$\begin{aligned} \text{Incomplete Scenarios: } \mathbb{E}_i[U_{ij} \mid \tilde{X}_j] &= \sum_{x \in A \setminus Q} \beta_i^x x_j + \beta_i^Q \mathbb{E}_i(Q_j \mid \tilde{X}_j) + \mathbb{E}_i(\epsilon_{ij} \mid \tilde{X}_j) \\ \text{Complete Scenarios: } \mathbb{E}_i[U_{ij} \mid X_j] &= \sum_{x \in A \setminus Q} \beta_i^x x_j + \beta_i^Q \mathbb{E}_i(Q_j \mid X_j) + \mathbb{E}_i(\epsilon_{ij} \mid X_j) \end{aligned} \tag{26}$$

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

$$\begin{aligned} \text{Complete Scenarios: } \mathbb{E}_i(Q_j \mid X_j) &= \sum_{x \in A \setminus Q} \gamma_i^x x_j + \gamma_i^R R_j + \mathbb{E}_i(\zeta_i \mid X_j) \\ \text{Incomplete Scenarios: } \mathbb{E}_i(Q_j \mid \tilde{X}_j) &= \sum_{x \in A \setminus Q} \gamma_i^x x_j + \gamma_i^R \mathbb{E}[R_j \mid \tilde{X}_j] + \mathbb{E}_i(\zeta_i \mid \tilde{X}_j) \\ &= \sum_{x \in A \setminus Q} \tilde{\gamma_i}^x x_j + \mathbb{E}_i(\zeta_i \mid \tilde{X}_j) \end{aligned} \tag{27}$$

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

$$\begin{aligned}\text{Complete Scenarios: } \mathbb{E}_i[U_{ij} \mid X_j] &= \sum_{x \in A \setminus Q} (\beta_i^x + \beta_i^Q \gamma_i^x) x_j + \mathbb{E}_i(\epsilon_{ij} \mid X_j) \\ \text{Incomplete Scenarios: } \mathbb{E}_i[U_{ij} \mid \tilde{X}_j] &= \sum_{x \in A \setminus Q} (\beta_i^x + \beta_i^Q \tilde{\gamma}_i^x) x_j + \mathbb{E}_i(\epsilon_{ij} \mid \tilde{X}_j)\end{aligned} \tag{28}$$

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

$$\begin{aligned}\Delta_{ijk} &= \sum_{x \in A \setminus Q} \underbrace{(\beta_i^x + \beta_i^Q \gamma_i^x)}_{\beta_i^{x(CS)}} (x_j - x_k) \\ \tilde{\Delta}_{ijk} &= \sum_{x \in A \setminus Q} \underbrace{(\beta_i^x + \beta_i^Q \tilde{\gamma}_i^x)}_{\beta_i^{x(IS)}} (x_j - x_k)\end{aligned} \tag{29}$$

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

$$\beta_i^{G(CS)} - \beta_i^{G(IS)} = \beta_i^Q (\gamma_i^G - \tilde{\gamma}_i^G) \tag{30}$$

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 the presence of belief-based discrimination against female managers, this should be negative. This is what our estimates show, given that individuals care positively about manager quality. Thus, under this model specification, belief-based discrimination is identified. Observe the analogy with the model presented in the main paper. Here, too, if the individual does not care about manager quality (i.e., $\beta^Q = 0$), the parameters identified from the complete and incomplete scenarios must be identical because the variation in information revelation will have no effect.

A.6 Details on survey administration and data collection

The online survey was designed and implemented on Qualtrics. Access to the internet was not a concern for our sample of 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 ensuring that it was mobile-friendly, in consideration of the fact that a small but significant proportion of the target population might not have access to a computer. Recruitment of students was done by the research assistants (RAs), who had previous experience in recruiting students for surveys and RCTs. 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 student class representative, who distributed the link in the class lists. The sign-up sheet, in addition to containing the consent form for them to sign, asked for e-mail addresses to which the link of the survey would be sent, as well as basic demographic information, department affiliation, faculty of study (arts/science/engineering) and level (bachelor's or master's) and year of study. The sign-up sheet described the survey as *"...an online survey on hypothetical job choices"* with the purpose described as *"...to better understand the preferences for the different attributes of jobs."*. 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 from April 8th to April 11th. On their selected date, they had a choice among 6 time slots: 10 am, 12 noon, 5 pm, 7 pm, 9 pm and 11 pm. We observed that our pilots that 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 respondents' enrollment form to their email address. This enabled us to automatically have the signed copy of the consent form sent to the participant.

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

Step 3: The mode and details of online payment were selected in the last section of the survey. The options included direct bank transfers, PayPal and UPI (unified payment interface). The payment was processed for the list of verified students within the prestated timeline for each payment mode.

A.7 Appendix Figures and Tables

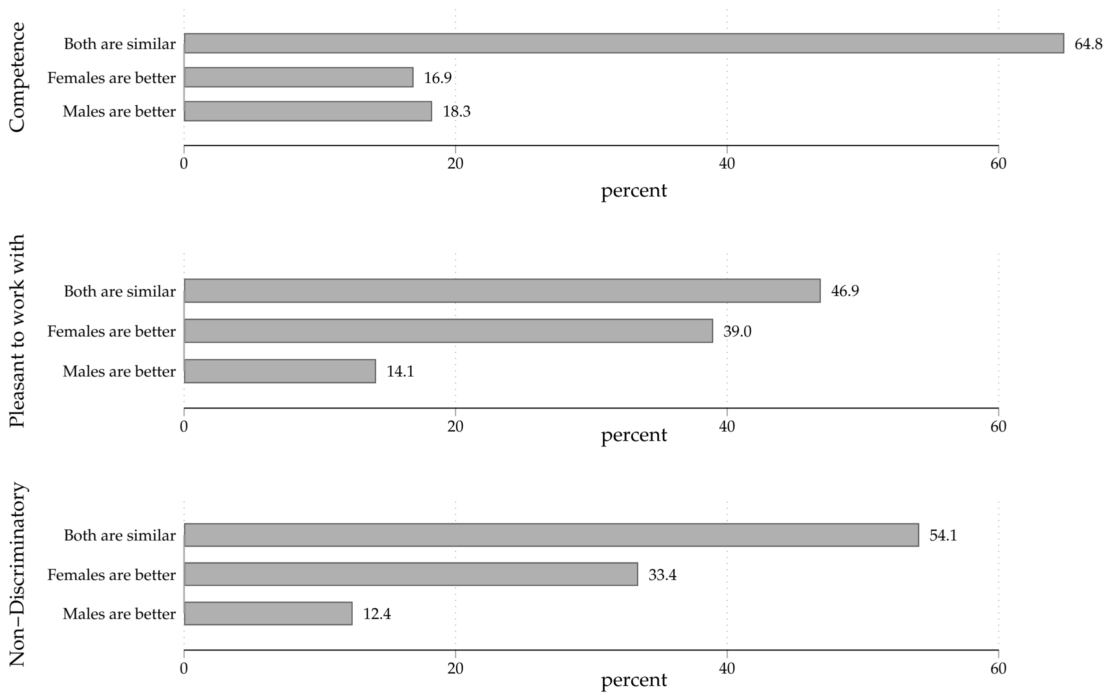


Figure A.1: Comparison of traits by gender

Table A.1: 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

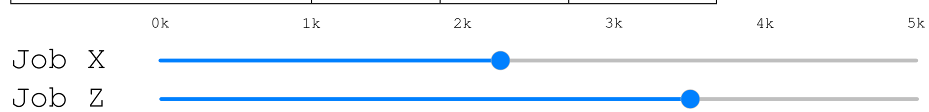
Job Y

Job Z

Compensating differential (*if job chosen was Y*)

You chose Job Y.
If you were to negotiate your wage, how much of a 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



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

Table A.2: 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

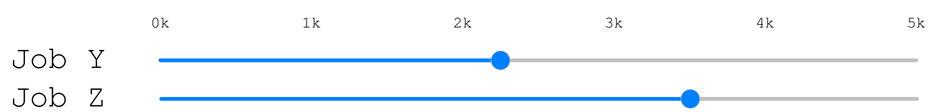
Job Y

Job Z

Compensating differential (*if job chosen was X*)

You chose Job X.
If you were to negotiate your wage, how much of a 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: Jobs X and Y have male managers, and Job Z has a female manager. Overall, across the 10 complete scenarios, five scenarios have two jobs with male managers and one job with a female manager, and the remaining five have two jobs with female managers and one job with a male manager.