WORKER-SIDE DISCRIMINATION: BELIEFS AND PREFERENCES

EVIDENCE FROM AN INFORMATION EXPERIMENT WITH JOBSEEKERS*

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July 2025

Abstract

Workers' preferences and beliefs shape labor market outcomes, yet remain understudied. We develop a theory-driven novel identification strategy for information experiments that separates beliefs from preferences. We apply this to provide the first evidence on the distribution of workers' preferences on manager gender, and their beliefs on managers' mentoring ability. 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—willing to forgo 1.3–2.2% of average annual wages. Hence, absent additional information, workers believe female managers are worse mentors (1.6% wage equivalent). Non-parametric estimates of the distributions reveal that 75% prefer female managers with mentoring information, and 67% believe male managers are better mentors absent information. Machine learning algorithms show that individuals with higher education are less likely to hold such beliefs. These beliefs are primarily driven by perceptions that women are less competent. Evidence suggests these beliefs are biased, highlighting scope for information-based policy interventions. Our identification-driven design provides a general framework for information experiments to study beliefs.

JEL codes: C81, J16, J71, J24, D83

Keywords: Mentorship, preferences, beliefs, information experiment, compensating differentials, worker-side discrimination.

*We are grateful to Chris Taber, Jeff Smith, Jesse Gregory and Matt Wiswall for helpful discussions, and guidance on the survey design. We thank Peter Arcidiacono, John Kennan, Limor Golan, Steve Lehrer, Rasmus Lentz, Lance Lochner, Corina Mommaerts, Laura Schecter, anonymous referees, and many seminar and conference participants for helpful comments. We thank Suraj Das, Iman Kalyan Ghosh, Kabir Rana, Shreya Seal and Aishani Sengupta for excellent research assistance in administering the pilots, debriefs and final survey. Any errors are our own. We acknowledge funding support for this research by the American University of Sharjah (Grant: FRG19-M-B41; IRB approval protocol number: 2019-509).

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1 Introduction

Managers differ considerably in their ability to manage and mentor workers, directly impacting workers' careers, wages and within-firm wage inequality, and retention (Frederiksen et al. 2020, Alfonsi et al. 2022, He & le Maire 2022, Acemoglu et al. 2022, Hoffman & Tadelis 2021, Lazear et al. 2015). While workers value and sort on many nonpecuniary job benefits (Dey & Flinn 2005, Blau & Kahn 2017, Mas & Pallais 2017, Wiswall & Zafar 2018, Taber & Vejlin 2020), and despite substantial public and private investment in mentoring programs,[1] how manager gender and their mentoring quality influence workers' job choices—and whether workers are aware of the mentoring quality of managers—remains an open question. Crucially, observed gender gaps in mentoring outcomes often reflect gender gaps in resources (such as networks) rather than gender gaps in mentoring ability (Schwartz et al. 2022), but worker beliefs about gender gaps in mentorship are unknown.

The job choice of workers, especially jobseekers, depends on—in addition to their preferences—their beliefs (Robinson 1933, Jäger et al. 2021) because they may not have complete information about their managers. Information and search frictions contribute to suboptimal labor market matches (Heller & Kessler 2024, Banerjee & Chiplunkar 2024) and implicitly assuming workers have correct beliefs can bias policy design and generate welfare losses (Conlon et al. 2018). Understanding the distribution of these preferences and beliefs is essential for designing effective information interventions and understanding gender-based sorting in labor markets, particularly given high training and turnover costs. Additionally, if workers' preferences and beliefs lead them to avoid female managers, they would require wage premiums to accept such positions, thereby strengthening glass ceilings and widening gender gap at managerial positions in equilibrium.

In this paper, we provide novel evidence on the distributions of worker preferences over manager gender and beliefs about managers' mentoring ability. We focus on mentoring given extensive evidence of its impacts: mentorship enhances human capital accumulation (Falk et al. 2020), wage expectations (Boneva et al. 2021), productivity (Blau et al. 2010), collaborative networks (Ginther & Na 2021), and promotions (Lyle & Smith 2014), and helps minorities break glass ceilings (Athey et al. 2000, Müller-Itten & Öry 2022).[2] We define worker-side discrimination—in the spirit of a

[1] For example, the U.S. Department of Justice funds nationwide youth mentoring programs, New York City's Young Men's Initiative provides mentoring at the local level, and public-private partnerships like the Massachusetts Mentoring Partnership coordinate mentoring initiatives statewide. Also see the report on private sector engagement in mentoring by EY and The National Mentoring Partnership (MENTOR) available at: https://www.mentoring.org/wp-content/uploads/2019/12/EY_Full_Report-1.pdf

[2] The American Economic Association's CeMENT program, where senior women faculty mentor junior women faculty, exemplifies in-group mentoring initiatives.

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 extending Becker (1971)'s conceptualization.[3] This willingness to trade off wages is driven by preferences for observable attributes and beliefs about unobservable attributes that workers care about but lack 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 omitted variables in general do not confound our results (Blass et al. (2010), Wiswall & Zafar (2018), Ameriks et al. (2020), Fuster et al. (2021), Koşar, Ransom & Van der Klaauw (2021), Koşar, Şahin & Zafar (2021)).[4] Hypothetical choice methods are attractive because they allow unrestricted preference heterogeneity (Blass et al. 2010), enable researchers 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, Andrew & Adams 2025).

To separately identify the distribution of beliefs, we embed a within-worker information experiment where we exogenously vary the observability of managers' mentoring quality. We measure mentorship quality using a five-point rating scale, reflecting firms' growing reliance on manager ratings (Cai & Wang 2022).[5]

We conduct our hypothetical choice survey and information experiment among job-seeking students at a highly selective university in India one year before graduation. We present respondents with twenty sequential job choice scenarios, each requiring them to choose among three jobs and report wage compensating differentials that would make them indifferent between their preferred job and the alternatives. Jobs are exogenously varied along four realistic attributes: annual wages, flexible hours, manager gender, and manager mentorship quality.[6] This generates panel data on choices and compensating differentials providing us nonparametric cardinal measures across the support of job attributes.

[3] 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 wage differentials.

[4] Worker heterogeneity in preferences on various dimensions of job attributes, many of which are unobservable to the researcher, are difficult to isolate using data on realized job choices. However, such data have advantages for studying employer discrimination, as employers typically value consistent worker attributes.

[5] Google, e-Bay, and Amazon collect anonymous employee surveys rating managers. Comparably, Completed, TheJobCrowd and Kunukunu are some 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. Panel data on choices and compensating differentials over the support of job attributes provide identifying variation for estimation of flexible models.

To circumvent potential social desirability bias in eliciting beliefs about manager mentorship conditional on gender, we implement a within-individual information experiment. In the first ten scenarios ("incomplete scenarios"), respondents observe three job attributes—annual wages, flexible hours, and manager name—with mentorship ratings listed but marked as unavailable. In the final ten scenarios ("complete scenarios"), respondents observe all four attributes including mentorship ratings. Following standard practice, 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)).[7] Given our novel design, we add a crucial instruction that compensating differentials only increase wages without changing anything else about the job.

We use our unique panel data on choices and compensating differentials to estimate a structural model of job choice where worker preference and valuation of belief parameters can be expressed as willingness to forgo wages. In incomplete scenarios, workers form conditional expectations about unobserved mentorship ratings, so their responses reflect both preferences and beliefs about mentorship conditional on other attributes. In complete scenarios, workers observe all attributes, so responses reflect only preferences. This variation in information availability for each individual identifies individual-specific preferences from within-complete-scenario variation, and between-complete and incomplete-scenario variation identifies individual-specific beliefs, allowing us to identify the full distributions of both parameters.

We find that absent 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 reflect *only preferences*, workers prefer to work for female managers, willing to forgo 1.7% of average annual wages to work for them. This reveals that workers believe female managers are worse mentors: we estimate these negative beliefs to be worth 1.6% of average annual wages, offsetting the preference for female managers in the incomplete scenarios.

Our average estimates mask substantial heterogeneity. Using our within-worker design we estimate individual-specific parameters, and apply nonparametric empirical Bayes shrinkage with log-splines to avoid overstating variance from noisy estimates (Efron 2016, Walters 2024). We find that 75% of individuals prefer to work for female managers, while 67% believe female managers are worse mentors than male managers when mentorship information is unavailable. To identify systematic predictors, we use LASSO and find that respondents with advanced degrees (MPhil and

[7] This is one of the key advantages of using the hypothetical choice methodology over audit study field experiments. We also ask direct and indirect questions later in the survey to test how closely these instructions are followed.

PhD) and those whose mothers exceed fathers in educational attainment (specifically fathers with master's and mothers with above-master's degrees) are less likely to hold negative beliefs about female managers' mentoring ability.[8] LASSO selects no systematic demographic predictors for preferences, suggesting they are driven by idiosyncratic factors rather than observable group characteristics.[9]

To explore potential mechanisms behind the beliefs about gender gap in mentorship, we collected additional data on gender-specific perception of three traits: competence, pleasantness to work with, and non-discriminatory behavior. We extend our model to allow beliefs about mentorship quality to depend on these latent traits allowing us to quantify how much of the gender gap in mentorship beliefs arises through perceived differences in these traits. We find that competence is a significant predictor of mentorship, while the other traits are not. Since males are perceived to be more competent, this channel explains 44% of the negative beliefs on female mentorship. Crucially, conditional on these traits, negative beliefs on female mentorship reduces by 65.2%, suggesting that beliefs on gender gaps in mentorship are largely driven by perceived trait differences. Allowing workers to have preferences on these additional traits shrinks the preference on manager's gender by more than half. This highlights a conceptual strength of our extended framework that empirically engages with concerns discussed in Heckman (1998) on the interpretability of preferences once all dimensions except biological gender are equalized. As we condition on more gender-specific traits, thus making men and women more similar, "pure" gender preferences reassuringly decline.

Are these average negative beliefs on female managers' mentorship ability biased? While we cannot definitively answer this in absence of population data on manager mentorship quality in India, understanding potential bias is crucial for policy design: accurate beliefs require no intervention, while biased beliefs create welfare losses through suboptimal sorting. An extensive body of evidence from diverse contexts—including academia, entrepreneurship, and corporate settings—consistently shows that female mentors are at least as effective as male mentors, and often more so, particularly for female mentees. This strongly suggests that the negative beliefs we document are likely biased.

Consequently, information based interventions correcting these biases could improve welfare through multiple channels. First, they could directly improve worker-firm matching efficiency by enabling workers to sort based on true rather than biased mentorship beliefs. Second, heterogeneity results suggest specific targeting of such interventions at workers without advanced degrees, and those from households where

[8]We also find that those with unemployed fathers hold fewer negative beliefs, though this association is approximately one-third the magnitude of both the education effects.

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

fathers exceed mothers in educational attainment. Third, using a simple model of monopsonistic labor markets adapted from Card et al. (2018), Lamadon et al. (2022), we show that information provision can reduce gender gap in management levels in monopsonistic labor markets. Considering the share of female managers and average firm mentorship as amenities, in presence of information on manager mentorship, firms by hiring more female managers vertically differentiate themselves, attract more workers and reduce equilibrium wage bill. This market-based mechanism can also reduce gender gap at management levels resulting from firm discrimination, where reduced wage bill partially offset discrimination costs.

To validate our information experiment approach, we also directly elicit mentorship beliefs by asking respondents to rate managers in hypothetical jobs. Direct elicitation yields opposite results: respondents report female managers as better mentors. This reversal is driven by male respondents. Importantly, these directly elicited beliefs contradict the raw choice data where approximately 20% more jobs with female managers are chosen in complete versus incomplete scenarios, indicating negative beliefs about female mentorship. This pattern suggests that direct belief elicitation suffers from social desirability bias—consistent with evidence of social desirability bias in the contexts of socially sensitive topics[10]—validating our indirect approach to identify beliefs.[11]

Our paper contributes to multiple strands of the literature. Methodologically, we develop a novel identification strategy for information experiments and implement it within the stated-preference literature. While existing methods identify preferences when individuals have complete information—applied to electricity services (Blass et al. 2010), jobs (Wiswall & Zafar 2018), residential locations (Koşar, Ransom & Van der Klaauw 2021), political candidates (Delavande & Manski 2015), and insurance products (Boyer et al. 2017)—we advance this literature in three ways. First, we introduce an information experiment that systematically varies the availability of attribute information across scenarios, to separately identify preferences and beliefs about unobserved attributes. Second, we elicit wage compensating differentials rather than choice probabilities. We formally show that choice probabilities under varying information structures require non-innocuous normalizations that prevent identification, while compensating differentials—as monetary valuations—remain invariant across information conditions, enabling identification. Our identification strategy provides a general framework for researchers broadly applicable across contexts where informa-

[10]See Bursztyn et al. (2025) for an excellent review on social desirability bias

[11]While the reversal in directly elicited beliefs could reflect learning from our gender-balanced mentorship ratings, such learning would predict equal assessments of male and female managers, inconsistent with the observed pattern of directly elicited beliefs. Later in the paper, we also discuss contexts where social desirability bias is less of a concern, and thus direct elicitation methods being more straightforward, should be preferred.

tion provision affects decision-making through beliefs. In concurrent work Andrew & Adams (2025) show identification of subjective beliefs which are probabilities about individuals' own future choices. Our paper fundamentally differs by focusing on individual's beliefs about others—specifically workers' gender-related beliefs about managers' quality measured as a continuous random variable. Third, our approach provides a method for eliciting beliefs where social desirability bias concerns exist. By using an information experiment to indirectly elicit beliefs, we mitigate the risk of respondents shading their responses toward socially acceptable ones.

To the best of our knowledge, we provide the first evidence on the distribution of worker beliefs on gender gap in mentorship prior to job matching. While extensive research documents that female mentors are at least as effective as male mentors across diverse contexts—in academia (Schwartz et al. 2022, Blau et al. 2010, Ginther & Na 2021, Carrell et al. 2010, Canaan & Mouganie 2021, Kjelsrud & Parsa 2024), corporate settings (Cardoso & Winter-Ebmer 2007, Kunze & Miller 2017, He & le Maire 2022) in entrepreneurship (Germann et al. 2024) and general labor market outcomes (Alfonsi et al. 2022)—we show that majority of workers nonetheless believe female managers are worse mentors suggesting that these beliefs are likely biased. Thus, while prior literature focuses on gender gaps in mentor effectiveness post-match, we identify the pre-match belief distribution that when biased may prevent optimal mentor-mentee matching. This is particularly consequential given the substantial value workers place on mentorship quality, which we quantify for the first time in the literature, marking our next contribution.

Despite extensive evidence on the positive impacts of mentorship on outcomes of mentees in academia, the corporate sector, the military, entrepreneurship and schools (Athey et al. (2000), Blau et al. (2010), Lyle & Smith (2014), Falk et al. (2020), Müller-Itten & Öry (2022), Germann et al. (2024), Boneva et al. (2021)), ours are the first estimates of workers' willingness to pay for better mentors. We estimate that individuals will forgo up to 5.65% of average annual wages for a one-standard-deviation increase in mentorship rating. The magnitude reflects the high value early-career workers place on mentorship underscoring the non-trivial impact of any biased beliefs on mentorship quality. Over-subscription typically seen in mentoring programs (see for e.g., Athey & Palikot (2022)), highlights strong preference consistent with the magnitude of our estimates. This strong preference for quality mentors is crucial for our identification: if workers did not value mentorship, any belief distribution could rationalize the data, making beliefs fundamentally unidentified.

Our evidence on worker preferences and beliefs conditional on manager's gender contributes to the discrimination literature, where worker-side discrimination has received little to no attention.[12] While Flory et al. (2015) find that manager gender

[12]Recent work by Abel (2019), Abel & Buchman (2020) and (Ayalew et al. 2021) study how managers'

does not impact application decisions, our analysis reveals that this finding is sensitive to the information that workers have about managers, and that there exists substantial heterogeneity in this regard. Next, the literature on discrimination typically 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 et al. (2021) estimate the distribution of racial discrimination, but they consider discrimination by firms toward workers. To the best of our knowledge, our 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 et al. 2019) as a measure of the willingness to forgo wages.[13] Finally, in our policy section we discuss how information interventions that correct worker's biased beliefs can reduce gender gaps in management arising from firm discrimination.

We also add to the literature on social desirability bias in two ways. First, we show that consistent with the existing evidence, direct elicitation methods are susceptible to social desirability bias while studying sensitive topics like gender, race, corruption, discrimination and sexual behavior (Bursztyn et al. 2025, Björkman Nyqvist et al. 2018, Kraay & Murrell 2016, Hainmueller & Hangartner 2013, Kuklinski et al. 1997). Second, we find that men are particularly susceptible to social desirability bias when studying beliefs on gender.

Finally, our work contributes to the growing literature on online surveys and experiments (Stantcheva 2022) with information treatments to study beliefs (Wiswall & Zafar (2015), Kuziemko et al. (2015), Alesina et al. (2019), Boneva & Rauh (2018), Alesina & Stantcheva (2020), Stantcheva (2021), Alesina et al. (2021), Coibion et al. (2022)).

The paper proceeds as follows. Section 2 describes our hypothetical job choice survey and information experiment. Section 3 presents the sample and data patterns. Sections 4 develops the job choice model and Section 5 shows identification using compensating differentials. Section 6 explains estimation and inference. Section 7 presents our main estimates and heterogeneity analyses. Section 8 examines how gender-specific trait perceptions explain our results. Section 9 discusses whether beliefs are biased followed by policy implications in Section 10. Section 11 delves into further discussions including direct elicitation results, and Section 12 concludes.

job performance affects workers' willingness to follow advice—distinct from our focus on mentorship quality given evidence on its direct impact on subordinate outcomes (Hoffman & Tadelis 2021) and the Peter principle (Benson et al. 2019).

[13] Bohren et al. (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.

2 Institutional Context, Hypothetical Job Choice Survey and Information Experiment

We administered our survey to students at a highly selective public university in India who were one year away from graduation. This population allows us to focus on high-skill jobseekers. A key institutional feature of campus recruitment in such universities is that candidates typically learn the gender of their prospective manager during final-stage interviews, before accepting job offers.[14] While individuals may switch jobs or teams over time, we intentionally sample those not yet in the labor market to avoid idiosyncratic shocks that may confound their true underlying parameters.

Our hypothetical job choice survey consisted of four parts: (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. We describe each component in detail below.

2.1 Instructions

The first part of the survey presented definitions of the exogenously varied job attributes—manager name, annual wages, flexible hours, and manager rating—as shown verbatim in Figure F.1a. Manager rating was 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 to their subordinates."* followed by the description of the numeric five-point scale. Such anonymous employee surveys are standard practice in large firms such as Amazon, Google, and eBay,[15] and were similarly used in the field experiment of Cai & Wang (2022).

We then presented respondents with instructions that support our identification strategy (see Appendix Figure F.1b; Wiswall & Zafar (2018), Koşar, Şahin & Zafar (2021)). Two key instructions were emphasized. First, jobs did not differ along any attribute "*...NOT MENTIONED...*" in the survey. Second, reported wage increases should be interpreted as affecting only pay, with all else about the job held constant. These instructions were reiterated within each scenario. Respondents were next shown two example scenarios before beginning the main survey.

[14] See Online Appendix A.1 for further institutional details on campus recruitments and Online Appendix A.2 for details on the administration and implementation of the survey.

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

2.2 Job Choice Scenarios with Compensating Differentials

Each respondent completed twenty hypothetical job choice scenarios. In each, they selected one of three jobs and then reported the minimum wage increase required to make them indifferent between their chosen job and each of the two unchosen jobs—referred to as compensating differentials. The first 10 scenarios formed the "incomplete" set, in which manager mentorship ratings were mentioned but not shown. The final 10 were the "complete" scenarios, where ratings were provided. This within-subject variation forms the core of our information experiment. Respondents entered compensating differentials using a slider ranging from 0 to 2 lakh INR (≈ $2,857). If their required compensation exceeded 2 lakh, they were prompted to enter a higher value on a subsequent screen.[16] Tables 1 and 2 show representative examples from the incomplete and complete sets, respectively. For U.S.-adapted examples see Appendix Tables F.1 and F.2.

Table 3 presents descriptive statistics of the job attributes (Panel A), balance across manager gender (Panel B), and balance across complete and incomplete scenarios (Panel C). Across the 20 scenarios, respondents saw 60 unique jobs, evenly split between male and female managers and balanced across complete and incomplete scenarios. While variation in job attributes was exogenous, it was not fully random—scenarios were designed to avoid dominant options (Wiswall & Zafar 2018). Approximately half the jobs offered flexible hours. Average annual wages were 7 lakh INR (≈ $39,444 in PPP), consistent with offers to past graduating cohorts at the sampled university. The variation in wages was deliberately small, reducing concerns that some jobs might be interpreted as entry- vs. senior-level. The average mentorship rating in complete scenarios was 3.41.[17]

2.3 Remaining Parts of the Survey

Direct Belief Elicitation: Following the 20 job choice scenarios, we directly elicited respondents' beliefs about manager mentorship ability. This exercise allows us to compare beliefs inferred from the information experiment with those elicited directly. Respondents were shown 10 jobs—each with a manager's name, wage, and flexibility status—and asked to report each manager's mentorship ratings on a 0–5 sliding scale that they expected (see Appendix Figure F.3).

[16] We did not find any evidence of any design-induced bunching of reported compensating differentials at the boundary of the slider. We thank Jeff Smith for bringing our attention to check this.

[17] We return to the informativeness of the rating in the results section, where we address concerns of other interpretations that could have stemmed from not providing more context about the jobs.

Demographic Questions: The final section of the survey collected demographic information on respondents' field of study (arts, science, or engineering), family income, and parental education and occupation. We also included questions to assess whether respondents followed the survey instructions. The survey concluded with a prompt to select a preferred mode of online payment and its associated details for compensation of INR 500 ($\approx$ \$24 in PPP).[18]

2.4 Key Highlights of our Design

This subsection outlines key elements of our hypothetical job choice survey and the embedded information experiment that enable identification of beliefs and preferences from reported choices and reported compensating differentials.

In Section 5.3, we discuss why the presence of incomplete scenarios to identify beliefs requires compensating differentials rather than choice probabilities. This results from choice probabilities requiring non-innocuous normalizations. See Appendix B for a formal proof.

To signal and vary gender, we used only managers' first names. In the Indian context, last names can reveal other social identities like caste and/or religion. By omitting them, we avoided unintended variation across social categories. All names used were common and unambiguously male or female, ensuring that gender was the only varying dimension. This approach avoids potential confounds that arise in other contexts, such as the U.S., where first names may correlate with both gender and race (e.g., Bertrand & Mullainathan (2004), Kline et al. (2021)).

A key advantage of our design is that we observe the full choice set by construction. For each scenario, we know which job was chosen. The compensating differentials for the unchosen jobs 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 also allow us to directly estimate and interpret the parameters as measures of willingness to pay or to forgo wages.[19]

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 within-subject design allows us to recover the distributions of preferences and beliefs and not just the first moment, which would have been the case had we used a between-subject design.

[18]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

[19]This can also be achieved with data on choice probabilities with an additional step to transform the estimates into willingness-to-pay measures.

In the incomplete scenarios, to avoid priming respondents to assume either similarity or systematic differences in manager ratings, we used the following wording: *"The rating of each manager may be different, but the data are not available."*

We use 20 scenarios to feasibly span and vary over the support of job attributes while managing cognitive load.[20] Asking respondents to choose among many jobs per scenario, and over a larger number of scenarios proved infeasible during piloting. Instead, we asked them to evaluate three options in each scenario across multiple scenarios. This generated rich panel data on choices and compensating differentials across jobs that exogenously vary in attributes.

3 Data

3.1 Sample Selection, Description and Comparison with the Population of Interest

Eligible participants were students no more than one year from graduation. A total of 604 individuals participated in the survey, of whom 591 completed it. We excluded 11 respondents who either could not be verified as students or completed the survey in under 15 minutes. The final sample comprises 580 students, 41.72% of whom identified as female.[21] The median completion time was 51.4 minutes.

Table 4 reports descriptive statistics. Among respondents, 44% were enrolled in arts and humanities, 33.3% in engineering, and 22.1% in science. Female students were predominantly in arts and humanities (67%), while male students in engineering (49%) and science (33%). We also observe gender differences in family background. On average, female respondents come from more socioeconomically advantaged households. This pattern is consistent with the evidence that gender gap in tertiary education is substantially lower in rich households than in poor households in India (Choudhury & Kumar 2024). Females from relatively more privileged households are less likely to face gender norm based social frictions, financial frictions, and have lower opportunity costs of time to attend colleges and universities (Sekhri et al. 2024). Our sample characteristics in terms of family income, and parental education is comparable to studies using data from other Indian colleges such as Dasgupta et al. (2022) who show their sample representativeness with the associated university population. The selective nature of the elite university of our sample reflects some differences when compared with the population of college and university students in India. Proportion of females

[20]Similar surveys use 8–24 scenarios (e.g., Wiswall & Zafar (2018); Koşar, Ransom & Van der Klaauw (2021)).

[21]We asked respondents to report their biological sex. We did not collect data on gender identities that differ from biological sex.

in Indian universities in the 2021-22 academic year was 5.3pp higher at 47% (Ministry of Education, Government of India 2023). The national average enrollment rate in Engineering was 11.8% and in Science was 14.8%. Proportions of our survey respondents majoring in Engineering, Science and Arts follow overall and gender-specific national patterns, although our sample is relatively over-represented in Engineering and Science, while being relatively under-represented in Arts and humanities, due to specialization.

3.2 Patterns in the Raw Data

We begin by examining how individuals' choices and reported compensating differentials vary across the complete and incomplete scenarios by manager gender. These descriptive patterns motivate the job choice model introduced in the next section.

Panel A of Table 5 reports the percentage of jobs chosen by manager gender. Choice patterns are similar across male and female respondents. In the incomplete scenarios—where mentorship information is withheld—jobs with male and female managers are chosen at similar rates. In contrast, in the complete scenarios, where mentorship ratings are shown, 61.1% of jobs chosen have female managers—a 20 percentage point increase relative to male-managed jobs.

Panel B reports average compensating differentials for unchosen jobs by manager gender. In the incomplete scenarios, respondents demand 6.3 thousand INR ($\approx$ \$300) more to choose jobs with female managers over male managers. This pattern reverses in the complete scenarios: respondents now require 6.1 thousand INR ($\approx$ \$290) more to switch from a female-managed to a male-managed job. Both differences are statistically significant at the 1% level. While these unconditional comparisons involve only unchosen jobs, they are informative. A fuller interpretation requires modeling both the extensive margin (choice) and the intensive margin (compensating differential) as functions of job attributes. This is precisely what our job choice model does. Finally, before turning to the model, we address a natural question in this setting: are female respondents more likely to choose jobs with female managers?

3.3 Testing for In-Group Preferences

We next ask whether female respondents are more likely than male respondents to choose jobs with female managers. We test this using a difference-in-differences strategy applied to data from the complete scenarios.

Let $i = 1, \ldots, N$ index individuals, $j = 1, \ldots, J$ index jobs, and s index scenarios. Define $Choice_{ijs}$ as an indicator equal to 1 if individual i chooses job j in scenario s, and 0 otherwise. We estimate the following model:

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

Here, g_i is respondent i's gender, and $MG_{j(s)}$ is the gender of the manager in job j of scenario s. The vector $Attributes_{j(s)}$ includes all job attributes other than manager gender—annual wages, flexible hours, and mentorship rating. $Demographics_i$ includes the respondent's background characteristics. We include 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 model using a logit specification and bootstrap standard errors at the individual level.

Table 6 presents the marginal effect estimates from equation (1). We find no evidence that female respondents are more likely to choose jobs with female managers. This is consistent with the raw data, which also show no systematic gender differences in choices or compensating differentials. As expected, respondents are more likely to choose jobs with higher wages, flexible hours, and higher mentorship ratings.

We now turn to the structural model of job choice, which allows us to formally incorporate compensating differentials and isolate the role of beliefs in the absence of information about manager mentorship from the role of preferences. Our model enables us to estimate individual-level preference and belief parameters, interpreted in monetary terms as percentages of average annual wages.

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

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

where ϵ_{ij} denotes all unobservables that affect the utility of individual i from job j. Individuals use expected utilities while reporting their job choice and the corresponding compensating differentials.

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. 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 E and monotone transformations is shown in Appendix E.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.

4.2 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 uses their their beliefs $R_j = \widetilde{X_j}' \alpha_i^x + \eta_j$ 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.[22] 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

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

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

$$\widetilde{\beta}_i^x \equiv \beta_i^x + \beta_i^R \alpha_i^x \tag{7}$$

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 by exploiting variation in the reported compensating differentials within and between the complete and incomplete scenarios.[23] Through survey instructions (presented verbatim in Appendix Figure F.1b), individuals were instructed to assume that:

> **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

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

[23]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.

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.[24] 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 Preference Parameters

We show the identification of the preference parameters β_i^x for all $x \in \{G, H, R\}$ leveraging variation in compensating differentials within the complete scenarios.

Implication of Assumption (1): The instructions imply that unobservables across different jobs in conditional expectations are the same within each scenario. For every individual i and every job $j \neq k$ within each complete scenario,

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

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,

$$\mathbb{E}_i(\epsilon_{ik} \mid X_k, \Delta_{ijk}) = \mathbb{E}_i(\epsilon_{ik} \mid X_k) \tag{8}$$

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

$$\begin{gathered} \mathbb{E}_i(U_{ij} \mid X_j) = \mathbb{E}_i(U_{ik} \mid X_k, \Delta_{ijk}) \\ \Delta_{ijk} = (X_j - X_k)'\beta_i \end{gathered} \tag{9}$$

Since $(X_j - X_k)$ is of full rank for all j, k ensured by our survey, the preference parameters $\beta_i \equiv \{\beta_i^G, \beta_i^H, \beta_i^R\}$ are identified from the variation in the reported com-

[24] See Heckman (1998) for more discussion on the use of audit studies in detecting discrimination.

pensating differentials in the complete scenarios under assumptions (1) and (2) as long as

5.2 Belief Parameters

We show identification of the belief parameter vector $\alpha_i \equiv (\alpha_i^G, \alpha_i^H, \alpha_i^W)'$ for each individual i, leveraging 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,

$$\mathbb{E}_i(R_k \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) = \mathbb{E}_i(R_k \mid \widetilde{X}_k) \tag{10}$$

Thus, the expected utility from job k taking into account the compensating differential of $\widetilde{\Delta}_{ijk}$ along with the beliefs about mentorship in equation (5) and normalizing β_i^W to 1 is:

$$\begin{aligned}
&\mathbb{E}_i(U_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) \\
&= \beta_i^G G_k + \beta_i^H H_k + (W_k + \widetilde{\Delta}_{ijk}) + \beta_i^R \mathbb{E}_i(R_k \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) + \mathbb{E}_i(\epsilon_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) \\
&= \beta_i^G G_k + \beta_i^H H_k + (W_k + \widetilde{\Delta}_{ijk}) + \beta_i^R \mathbb{E}_i(R_k \mid \widetilde{X}_k) + \mathbb{E}_i(\epsilon_{ik} \mid \widetilde{X}_k) \\
&= \sum_{x \in \widetilde{X}} (\beta_i^x + \beta_i^R \alpha_i^x) x_k + \widetilde{\Delta}_{ijk} + \mathbb{E}_i(\epsilon_{ik} \mid \widetilde{X}_k)
\end{aligned} \tag{11}$$

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 k conditional on the compensating differential $\widetilde{\Delta}_{ijk}$ under A1, we have

$$\begin{aligned}\mathbb{E}_i(U_{ij} \mid \widetilde{X}_j) &= \mathbb{E}_i(U_{ik} \mid \widetilde{X}_k, \widetilde{\Delta}_{ijk}) \\ \widetilde{\Delta}_{ijk} &= \sum_{x \in \widetilde{X}} \underbrace{(\beta_i^x + \beta_i^R \alpha_i^x)}_{\equiv \widetilde{\beta}_i^x}(x_j - x_k)\end{aligned} \tag{12}$$

Thus, once β_i^x and $\widetilde{\beta}_i^x$ are identified, α_i^x is identified $\forall x \in \widetilde{X}$ as long as $\beta_i^R \neq 0$ and $\widetilde{X}_j - \widetilde{X}_k$ is of full rank for all j, k.

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

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 (equation 9). In contrast, in the incomplete scenarios (equation 12), 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.

Note that there are two circumstances when beliefs α_i^x are not identified. The first is when i does not care about mentorship ability i.e., $\beta_i^R = 0$. The intuition is that if individuals do not care about manager mentorship, then any belief distribution can rationalize the observed data. This makes the variation in the observed choices and compensating differentials independent of mentorship skill. The second, is when individuals believe mentorship is independent of all observed attributes. 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 proceeding to estimation, we address why identification—and consequently our survey design—relies on compensating differentials rather than choice probabilities or ranks commonly used in stated preference literature. This distinction has implications for designing information experiments to identify beliefs across economic contexts.

Choice probability data require assumptions about idiosyncratic taste shocks (typically Type I extreme value) and an associated variance normalization—standard in discrete choice models when all scenarios provide complete information. However, any design such as ours that requires variation of information structures fundamentally changes the expected utility formation of individuals that drive their choices in scenarios with different information structures. In incomplete scenarios, individuals form beliefs about unobserved mentorship quality, introducing additional unobserved uncertainty absent in complete scenarios. The total variance of unobserved expected utility components thus differs systematically between complete and incomplete scenarios. Incomplete scenarios contain both idiosyncratic taste shocks and belief-formation uncertainty, while complete scenarios contain only the former.

With choice probabilities, researchers must normalize variance in both scenario types. Since the underlying variance structures differ, these normalizations become non-innocuous. Thus, one cannot distinguish whether differences in choice probabilities reflect belief parameters or normalization artifacts. Appendix B provides the formal proof. This non-identification result persists even with parametric assumptions (e.g., normal distributions for both components; see Appendix B.1).[25]

Compensating differentials achieve identification because monetary valuations remain invariant across information structures. A dollar forgone represents the same expected utility loss regardless of information availability, enabling direct comparison across scenarios without confounding scenario-specific variance normalizations.

6 Estimation and Inference

The compensating differentials are reported with two different but independent measurement errors. First, respondents report in multiples of five (Figure 2). This is also common in surveys asking for choice probabilities (Blass et al. 2010). Second, the slider interface introduces random error despite displaying exact amounts. Under classical measurement error assumptions on both, these affect only standard errors, not consistency.

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:

$$\begin{aligned} \Delta^*_{ijk} &= \sum_{x \in X} \beta^x_i (x_j - x_k) + e_i \\ \widetilde{\Delta}^*_{ijk} &= \sum_{x \in \widetilde{X}} (\beta^x_i + \beta^R_i \alpha^x_i)(x_j - x_k) + \widetilde{e}_i \end{aligned} \tag{14}$$

[25] Using rank data is always dominated—even in complete scenarios—because cardinal information provides richer information on the distribution of preferences to the researcher than ordinal information from ranks. Next non-identification with rank data follows similar steps after specifying a distribution of the unobserved part of the utility function.

Under classical measurement error:

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

We jointly estimate system (14) using constrained least squares normalizing $\beta^W_i = 1$. The equations have no constant by construction since they are derived from utility differences. We use the block bootstrap at the respondent level allowing for arbitrary correlation among responses within each respondent. See Appendix D for details.

7 Main Results

7.1 Model Estimates of Preference and Belief Parameters

We present estimates of preference and belief parameters from our job choice model. We first present estimates on the demand for mentorship quality, followed by preferences for manager gender, and finally beliefs about gender gap on mentorship. This ordering builds the logical foundation: understanding how much workers value mentorship is necessary for identification and for interpreting both gender preferences in presence of information on mentorship and beliefs about gender differences in mentorship ability in the absence of its information.

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.[26] For better interpretability, we also convert these to percentages of average annual wages.

7.1.1 Demand for Mentorship Quality

Workers highly value mentorship quality. Table 7 Panel A shows workers will forgo 11% of average annual wages (≈ $3,800 or 80 thousand INR) for a one-point increase in mentorship rating on our five-point scale. In standard deviation units, workers value a one-SD increase in mentorship at 5.65% of annual wages. This estimate could seem large at first glance. However, it is unsurprising 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.

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

A potential concern is whether the mentorship rating was informative to respondents.[27] Recall that the mentorship rating was presented in the survey as "... *the average rating of the mentorship of the manager, provided by this manager's current employees in an anonymous survey*." Although our scenarios do not specify job types or industries to reduce cognitive load, if respondents were thinking of jobs dominated by out-group workers or different job types that made the mentorship ratings uninformative, we would observe evidence of this in the data. By contrast, the lower limit of the 95% confidence interval on the preference for highly-rated mentors is 10.5% of average annual wages, far from zero. The detailed instructions and this evidence mitigate concerns that the mentorship ratings were uninformative to respondents.[28]

7.1.2 Preference for Working for Female Managers

Table 7 Panel A presents estimates from jointly estimating equation system (14). In complete scenarios, where all job attributes are observed, we identify pure preference parameters. The first key finding from the complete scenarios is a strong preference for female managers. On average, workers are willing to forgo approximately 12 thousand INR ($\approx$ \$570) or 1.7% of average annual wages to work for a female rather than male manager ($\beta^G = -0.119$). The 95% confidence interval ranges from 1.3% to 2.2% of average annual wages.

In incomplete scenarios, the "biased" estimate of the preference for male managers ($\tilde{\beta}^G$) is small and statistically indistinguishable from zero. This stark difference between complete (β^G) and incomplete scenarios ($\tilde{\beta}^G$) reveals that workers' indifference masks preferences for female managers being offset by negative beliefs about their mentorship ability. This is evidence of belief-based discrimination only if workers value mentorship quality—which we discuss next.

7.1.3 Beliefs on Gender Gap in Mentorship

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 (13). Table 7 Panel B column (1) shows that on average workers believe male managers have 0.14-point higher mentorship ratings than female managers (0.28 SD). 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 ($\beta_i^R \alpha_i^G$). This is obtained by the difference in the parameters

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

[28] There is less concern about alternative interpretations of mentorship. For example, it is unlikely that English majors would answer our questions by imposing on themselves the extra cognitive load of thinking about jobs outside their domain of specialization.

between the complete and incomplete scenarios: $\tilde{\beta}_i^x - \beta_i^x = \beta_i^R \alpha_i^x$ for all $x \in \{G, W, H\}$. In Table 7 Panel B column (2), we report that workers' negative beliefs about female mentorship are worth 1.6% of average annual wages ($\beta_i^R \alpha_i^G$).[29]

Note that 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, individuals believe that male managers are better mentors than female managers.

7.2 Heterogeneity

7.2.1 Distribution of Preference and Belief Parameters

We leverage our panel structure of individual data to estimate the model for each individual separately to obtain individual-specific estimates of preference and belief parameters. Raw individual-specific estimates reveal substantial heterogeneity: approximately 62% of workers prefer working for female managers, while 60% believe female managers are worse mentors when mentorship information is unavailable. However, these individual-level estimates are noisy—each set being estimated from 20 scenarios. To avoid overstating the variance in the distribution obtained from noisy estimates, while accounting for heterogeneous standard errors across workers, we implement a non-parametric empirical Bayes (NPEB, henceforth) shrinkage procedure.[30] We estimate the underlying distribution of the parameters using log-spline deconvolutions following Efron (2016) and discussed in Walters (2024), and account for the varying precision of individual estimates through their respective standard errors to produce precision-adjusted posterior means (see Online Appendix C for details).

The distributions of belief and preference parameters obtained from the NPEB estimates are plotted in Figure 3, Panels A and B respectively, overlaid on top of the distributions obtained from the raw estimates. While variance is reduced as expected, the key patterns discussed above persist. Absent information on mentorship, 66.72% of workers believe that female managers are worse mentors absent information, and 75.35% of workers prefer female managers in presence of information on mentorship quality.

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

[30] Unlike parametric shrinkage methods, the non-parametric approach allows the true distribution to exhibit arbitrary features such as multimodality or skewness.

7.2.2 Correlates of Parameters with Observable Characteristics

To examine whether the heterogeneity in discrimination parameters correlates systematically with worker characteristics, we employ a simple machine learning approach. We use LASSO (Least Absolute Shrinkage and Selection Operator) to select the most relevant predictors from our full set of demographic characteristics including gender, field of study, family income, parental education levels, parental employment status and their interactions. This approach has the advantage of reducing the dimensionality of demographics and thereby circumventing concerns about multiple hypothesis testing which would arise while directly testing associations with numerous demographic variables.[31] Following variable selection, we regress the NPEB parameter estimates on the LASSO-selected demographics to document how they correlate with observable demographics.

Table 8 presents the results. For beliefs on gender gap in mentorship, LASSO selects three variables: a parental education combination (those with fathers holding master's and mothers above-master's degree), own education (those with advanced degrees i.e., MPhil and PhD) and father's employment status. OLS estimates of NPEB belief estimates on LASSO selected variables reveal that respondents pursuing education beyond a master's degree are less likely to hold negative beliefs about female managers' mentoring ability. We also find individuals whose mothers are more educated than their fathers—specifically those with fathers holding master's and mothers above-master's degree—are less likely to hold negative beliefs about female managers' mentoring ability. Those whose fathers are unemployed also are less likely to hold such beliefs, though this association is approximately one-third the magnitude of both the education associations.[32] For preferences on manager gender, LASSO selects no demographic variables. The absence of systematic demographic predictors for preferences, despite substantial individual-level heterogeneity, suggests that preferences for manager gender are driven by idiosyncratic factors beyond observable characteristics.

Exposure to higher education is associated with a reduced likelihood of holding such beliefs, consistent with education reducing biased beliefs in other contexts, for example immigrants (Dylong & Uebelmesser 2024) and inflation (D'Acunto et al. 2023). When mothers attain higher education than fathers within a household, especially with advanced degrees, this plausibly signals high gender-specific abilities that counteract biased stereotypes about gender.

[31]The LASSO estimator solves $\min_\beta \frac{1}{2n}\sum_{i=1}^{n}(\hat{\theta}_i^{NPEB} - x_i'\beta)^2 + \lambda\sum_{k=1}^{K}|\beta_k|$, where $\hat{\theta}_i^{NPEB}$ represents the shrunk estimtes, x_i represents K-dimensional vector of individual characteristics, and λ denotes the penalty parameter. We determine the optimal λ via 10-fold cross-validation over a grid of 100 values, that minimizes mean squared prediction error.

[32]The mechanism underlying this association remains unclear without additional information about fathers' workplace experiences, that maybe transmitted to their children.

8 Other Managerial Qualities and Potential Mechanisms

Since our main results show that mentorship is highly valued, understanding the source of these beliefs is crucial. To study this, we consider additional gender-specific managerial traits, and extend the model of beliefs on mentorship by allowing it to also depend on other traits. This allows us to (a) quantify the weight respondents place on those traits in inferring mentorship quality in the incomplete scenarios, (b) quantify the share of the gender gaps in beliefs on mentorship arising through perceptions about gender gaps in other traits, (c) examine whether the beliefs on gender gap in mentorship persist after conditioning on these traits and (d) thereby explore mechanisms driving our main results. To this end, we collect additional data on individuals' perceptions of three other managerial qualities: competence, pleasantness, and non-discriminatory behavior where individuals report ordinal data on whether they perceive males to be better, similar, or worse than females in each of these traits.

In Appendix C we extend our model to incorporate these additional traits, and formally show a three-step semi-parametric identification using cross-sectional variation across reported perceived traits in addition to within individual variation across complete and incomplete scenarios in Appendix C.3. Estimation and inference similarly follows a three-step joint block-bootstrap process explained in Appendix C.4.

We document four key findings from the estimates of the extended model reported in Appendix Table F and explained in more details in Appendix C.5. First, individuals perceive that male managers are substantially more competent than female managers.[33] Second, we find that competence significantly predicts mentorship ability, while pleasantness and non-discriminatory behavior show no significant relationship with mentorship quality (Appendix Table F: Panel B, column 2). Third, we estimate the beliefs on gender gap in mentorship conditional on other managerial traits and compare them to our baseline estimates to understand how much the mentorship belief gap reduces conditional on other managerial traits. Specifically, supressing other job attributes to reduce notational clutter, we compare estimates of $\mathbb{E}[\beta_i^R R_j \mid G_j = F, \mathbb{Q}] - \mathbb{E}[\beta_i^R R_j \mid G_j = M, \mathbb{Q}]$ from our extended model where $\mathbb{Q}$ denotes the vector of other qualities, to our baseline estimates of $\mathbb{E}[\beta_i^R R_j \mid G_j = F] - \mathbb{E}[\beta_i^R R_j \mid G_j = M]$. While qualitatively similar, the beliefs on mentorship gap once conditioned on other managerial traits reduces to 0.6% of average annual wages (Appendix Table F: Panel C, column 1). This is a 62.5% reduction in comparison to our estimates from the baseline model. Fourth, we decompose the total valuation of the beliefs in mentorship gap and find that approximately 44% of the mentorship gap is driven by perceptions of gender-based trait differences (Appendix Table F: Panel C, column 2).

[33] See Appendix Table F: Panel B, column 1 and Appendix Figure F.2 for the estimated distributions in the perceived gender gap of the three latent traits.

An assumption underlying this decomposition is that respondents' reported perceptions of other managerial traits reflect their true perceptions. If social desirability concerns lead individuals to overstate the quality of females on traits, our estimates of gender gaps in these traits could be attenuated. In such a case, our estimate that 44% of the mentorship belief gap is explained by perceived traits is a lower bound. With workers valuing one SD of mentorship at 5.65% of wages, if their beliefs representing a 0.28 SD gender gap in mentorship—at least half of which are driven by perception that women are less competent—are inaccurate, they could create substantial welfare losses. Consequently, whether these beliefs and perceptions are accurate has important implications for policy.

9 Are Negative Beliefs About Female Mentorship Biased?

Our findings reveal that workers believe female managers are worse mentors than male managers, absent information about mentorship quality. While we lack data on the population distribution of mentorship quality by gender in India, wide range of evidence from other contexts documents that female mentors are at least as effective as male mentors, and often more so, especially for female mentees.

Early meta-analyses find economically small gender differences in mentoring effectiveness (O'brien et al. 2010). Observed gender gap in mentoring outcomes often reflects gender gap in resources available to mentors rather than gender gap in mentoring ability. Schwartz et al. (2022) show that conditional on available resources, no gender gap exists in mentoring effectiveness—observed differences stem from male mentors' greater access to resources like labs, grants and networks. Recent experimental evidence corroborates this conclusion. Alfonsi et al. (2022) find no significant differences in career trajectories between mentees of male versus female mentors in Uganda. In entrepreneurship, female mentors increase firm sales and profits of female entrepreneurs more effectively than male mentors (Germann et al. 2024). Using administrative data linking white-collar workers to their bosses across firms in Norway, Kunze & Miller (2017) find smaller gender gaps in promotion of workers working for female bosses than male bosses. Similar results have been documented by He & le Maire (2022) in Denmark where female managers are more likely to have higher manager-specific wage premium who in turn are documented to reduce overall within-firm wage inequality. In Portugal, Cardoso & Winter-Ebmer (2007) find female workers have higher wages in female-led firms than in male-led firms through higher female employer-worker mentorship. Increased representation of women in corporate leadership led to fewer worker layoffs within firms in Norway (Matsa & Miller 2013). In Germany, Boneva et al. (2021) find that female mentors reduced gender gap in earnings expectations by close to a quarter for girls from disadvantaged backgrounds. In academia, studies exploiting random or quasi-random mentor-mentee or advisor-advisee matching consistently find positive effects of female mentorship. Female professors substantially improve female students' STEM enrollment and graduation rates, and reduce dropout rates from PhD programs (Carrell et al. 2010, Canaan & Mouganie 2021, 2023). Leveraging variation in sabbatical timings to estimate mentorship impacts Kjelsrud & Parsa (2024) find that increasing senior female professors would close one-third of the assistant professor gender gap. The AEA's mentoring program, which matches senior to junior female economists, yields significant career benefits for mentees (Blau et al. 2010, Ginther & Na 2021). These findings suggest that workers' negative beliefs about female mentorship are likely biased. Consistent with this review of the mentorship literature—which finds no evidence of gender differences in mentorship ability—Weidmann et al. (2024) document that gender is not a significant predictor of overall managerial effectiveness.

Existence of biased beliefs is a well-documented common phenomenon. Individuals systematically misperceive population distributions across diverse contexts. People hold biased beliefs about the returns to education (Wiswall & Zafar 2015), form inaccurate stereotypes (Bordalo et al. 2016), misperceive immigration levels and immigrant characteristics (Alesina et al. 2019, Dylong & Uebelmesser 2024), misperceive social norms about female labor force participation (Bursztyn et al. 2018), and have incorrect expectations about economic indicators (D'Acunto et al. 2023). Similar biases appear in beliefs about discrimination (Bohren et al. 2019), racial and diversity statistics (Alesina & Stantcheva 2020), income distributions (Hvidberg et al. 2020), college returns (Bleemer & Zafar 2018), and gender gap in social preferences (Exley et al. 2025). Importantly, assuming workers hold correct beliefs when they do not can lead to suboptimal policy design (Conlon et al. 2018).

In our context, this matters quantitatively since workers are willing to forgo 5.65% of annual wages for a one-standard-deviation improvement in mentorship quality. Biased beliefs thus generate substantial welfare losses through suboptimal job matching, as driven by these potentially biased beliefs workers could avoid female managers despite their equal or in some cases superior mentoring effectiveness.

10 Policy Implications

10.1 Information Provision in Firms and Mentoring Programs

Our findings, combined with evidence that female mentors are at least equally as effective as male mentors, suggest a simple policy intervention of disclosure of manager ratings. Many firms already collect such data internally. Making these ratings transparent could correct biased beliefs, improve job matching efficiency. Our estimated valuation of one SD increase mentorship quality at 5.65% of average annual wages and documented evidence of the impact of manager quality on worker and firm outcomes indicate substantial gains from such information provision.

Our heterogeneity results directly inform targeting of such policies towards workers without advanced degrees and those from households with traditional educational hierarchies (fathers more educated than mothers) since they are more likely to hold negative beliefs about female managers' mentorship ability. Additionally, accounting for evidence that female mentors are more effective when paired with female mentees suggests that such information provision interventions could be particularly beneficial for female workers.

Such information provision could also enhance efficacy of mentoring programs in general. Potentially biased beliefs imply mentees under-match with female mentors, limiting program effectiveness. Providing aggregated mentee outcome statistics––such as career progression, skill development—would serve as credible signals of mentorship quality to correct potentially biased beliefs. Additionally, given our finding that workers perceive competence and mentorship ability are positively correlated, visible mentee success statistics would also signal mentor competence more broadly.

10.2 Gender Gap at Management Levels

Correcting beliefs through information-based interventions has implications for gender gap at management levels. Consider a labor market of imperfect competition, where the proportion of female managers and the average manager mentorship in a firm are firm amenities that vertically differentiates firms where male and female managers are equally effective mentors.

Imposing our empirical results, in absence of information, the elasticity of equilibrium wages with respect to female managers is zero since worker preferences and beliefs offset each other. So firms have no incentive to change the share of female managers. However, with transparent mentorship information, the biased beliefs are mitigated, and this elasticity becomes negative reflecting worker preferences. Thus, at the margin firms find it profitable to increase the share of female managers to enjoy reduced wage bill. See Online Appendix B for a simple theoretical discussion of this mechanism. This mechanism operates even in discriminatory firms that have preferences against hiring women in managerial positions. With information provision, workers' willingness to accept lower wages to work for female managers reduces wage bill that partially offset firms' discrimination costs, making discrimination more expensive to sustain. Indeed, the impact of information provision on gender gap in management between discriminatory and non-discriminatory firms will differ based on the nature of discrimination costs. See Online Appendix B.3.1 for more details on this extension.

11 Discussions

11.1 Methodological contributions, direct elicitation and broader applications

Our identification strategy using compensating differentials and comparing complete and incomplete scenarios provides a general framework for studying beliefs through information experiments across diverse economic contexts. The approach applies whenever information provision alters expected utility formation and the researcher is interested in studying beliefs. Elicitation of compensating differentials achieves identification. In labor markets, varying worker performance information and eliciting wage offers, researchers can study employer beliefs about worker quality by demographics. In healthcare, varying information about provider quality while eliciting compensating differentials in fees could reveal beliefs about physician competence across demographics. For technology adoption, withholding or providing efficacy data while measuring compensating differentials in price paid identifies beliefs that may limit adoption. In financial markets, our method could identify beliefs about investment risks by varying historical return information and measuring resulting portfolio allocations. In education markets, varying school quality metrics while eliciting compensating differentials in tuition reveals parental beliefs about school quality. This framework enables belief identification because monetary trade-offs reflect the value of information about unobserved characteristics.

Furthermore, we conduct a validation exercise which shows that direct elicitation methods are susceptible to social desirability bias while studying sensitive topics like gender, race, corruption, discrimination and sexual behavior consistent with existing evidence (Bursztyn et al. 2025, Björkman Nyqvist et al. 2018, Hainmueller & Hangartner 2013, Kuklinski et al. 1997, Kraay & Murrell 2016).

11.1.1 Direct elicitation of beliefs on gender gap in mentorship

After our information experiment, we also directly elicited beliefs on manager mentorship. Respondents evaluated 10 jobs with exogenously varied manager names, wages, and flexible hours (see Appendix Figure F.3). For each job, they reported their expected manager mentorship rating on a zero-to-five scale. Using these data we estimate $R_{ij}^{direct} = \theta_i + \alpha^G G_j + \alpha^H H_j + \alpha^W W_j + \eta_{ij}$ where R_{ij}^{direct} is individual i's directly elicited mentorship rating for the manager in job j, G_j indicates a male manager, H_j

indicates availability of flexible hours, W_j are annual wages, and θ_i is an individual fixed effect. Appendix Table F.4 presents the results. Directly elicited beliefs show the opposite pattern from our model-based estimates. Respondents when directly asked on average believe female managers are better mentors ($\hat{\alpha}^G = -0.042$, statistically significant at 1%). This is equivalent to -0.08SD in beliefs on gender gap in mentorship. This reversal is driven by male respondents ($\hat{\alpha}^G = -0.053$, statistically significant at 5%), while female respondents' directly elicited beliefs on gender gap in mentorship are statistically indistinguishable from zero.

This reversal—from negative beliefs revealed in the information experiment to positive beliefs on female mentorship when asked directly—validates our information experiment approach for studying beliefs. Furthermore, our model-based estimates are consistent with the raw choice data patterns where in presence of information on mentorship, jobs with female managers are chosen at substantially higher rates (by 20%) than in the absence of information suggesting negative beliefs on mentorship. While learning during our experiment could potentially influence directly elicited beliefs, our design rules this out as the primary explanation. Since we balanced mentorship ratings across manager genders, learning would lead to no gender gap in directly elicited beliefs. Instead, we observe a significant reversal favoring female managers, particularly among male respondents, pointing to social desirability bias as the primary explanation. This underscores the value of indirect elicitation methods for socially sensitive topics like gender, race, discrimination, and immigration, among others.

In other contexts where behaviors are less normatively sensitive or where social-image concerns are minimal, direct elicitation methods have been found to be reliable. For example, survey-based reports of educational attainment closely align with administrative records (Lamb Jr & Stem Jr 1978, Kleven & Ringdal 2020). Similarly, in the context of voting in Norway, a 96 percent match exists between self-reported turnout and registry data (Kleven 2022), suggesting that in high-trust settings with strong civic norms and minimal perceived judgment, direct elicitation can be accurate. In such cases, direct elicitation methods should be preferred to avoid the cost of conducting information experiments.

11.2 Mentorship as the primary measure of managerial quality

Our focus on mentorship quality reflects its economic significance for early-career professionals. Unlike experienced workers, early-career professionals depend on managers' developmental capacity for human capital accumulation and career progression (Athey et al. 2000). Our empirical results confirm this, showing that respondents value a one-standard-deviation improvement in mentorship at 5.65% of annual wages. Additionally, we also find that beliefs about mentorship are correlated with perceptions about manager competence more broadly. Furthermore, consistent with our review of the mentorship literature which finds no evidence of gender gap in mentorship, Weidmann et al. (2024) documents that gender is not a significant predictor of overall managerial effectiveness.

Our emphasis also aligns with evidence from the broader literature that effective mentorship improves labor market outcomes through various channels. Blau et al. (2010) show that structured mentoring enhances productivity and thereby promotions, while lack in mentorship negatively impacts career outcomes through absence of transmission of human capital (Kjelsrud & Parsa 2024). Ginther & Na (2021) and Schwartz et al. (2022) find that high-quality mentorship expands professional networks, and access to career enhancing resources. While mentorship is one aspect of managerial quality, its relevance to early-career labor market choices make it an appropriate and policy-relevant object of study.

11.3 Interpreting preferences for manager gender

It is hard to interpret gender preferences without assuming that males and females systematically differ along some dimensions. At the same time if it were theoretically possible to make all dimensions identical other than biological gender, any estimate of preferences on biological gender lacks interpretation. Similar thoughts are expressed in Heckman (1998).

Instead of delving into philosophical questions of what does it mean to be a male or a female all else equal, our analysis empirically engages with these conceptual challenges. Reassuringly, when we account for perceived differences in competence, non-discriminatory behavior, and pleasantness to work with, thereby equalizing men and women on more dimensions than our baseline estimate which only equalized them on mentorship, this preference estimate drops by more than half to 0.75% of wages (see Appendix C.5 and Panel A Column 2 Appendix Table F for more details). This suggests that much of what is typically discussed as "pure" gender preference reflects perceptions about gender-specific traits. Thus, our framework not only shows how belief- and preference-based components of discrimination or choices in general, can be empirically separated, but also provides a better understanding of interpretation of "pure" gender preferences.

11.4 Origins of gender versus racial bias

Our heterogeneity results highlight a fundamental difference between the origins of gender and racial bias. Unlike racial segregation, where individuals may lack exposure to other races, nearly everyone has exposure to women through family structures.[34] Yet our main results document potentially biased average negative beliefs on females. This suggests that mere exposure is insufficient and that the nature of exposure matters. Our heterogeneity analysis reveals that when mothers exceed fathers in higher education, children are less likely to have negative beliefs about females. This parallels findings by Alesina & Stantcheva (2020) that interracial contact by growing up in diverse neighborhoods reduces racial bias.

11.5 External validity and choices over the lifecycle

Our institutional context—elite Indian universities where campus recruitment typically reveals manager identity—ensures manager gender is typically observable before job acceptance. While not all labor markets share this feature, our setting is particularly relevant for tight labor markets where worker preferences matter most for firm outcomes. Similar information structures arise when job seekers use alumni networks, or when employees consider internal transfers, making our framework applicable beyond the specific context studied.

Our findings represent beliefs and preferences of job-seekers. This population and timing offer both advantages and limitations. Studying labor market entrants avoids confounding from idiosyncratic unobserved work experiences while capturing beliefs that drive sorting across industries and firms. The high valuation of mentorship naturally reflects first-time job-seekers' needs and would exhibit diminishing returns with experience. Since worker career paths are strongly influenced by their first-time employers even if workers switch (Arellano-Bover 2024), it underscores the importance of studying this population.

12 Conclusion

In this paper we develop and implement a theory-driven novel identification strategy that separates preferences from beliefs through within-individual information experiments. By systematically varying the availability of manager mentorship information in hypothetical job choices between complete and incomplete scenarios, we provide the first evidence on the distributions of worker preferences for manager gender and beliefs about mentorship ability. Methodologically, we demonstrate that compensating differentials succeed where choice probabilities fail in identifying beliefs when information varies. We identify preferences using the variation in compensating differentials within the complete scenarios. The variation in compensating differentials

[34] We thank Martha Bailey for sharing this parallel observation that growing up without a mother is not as common as living in a race-segregated neighborhood.

between the complete and incomplete scenarios identifies beliefs on mentorship skill.

We find that workers prefer female managers when fully informed, willing to forgo 1.7% of average annual wages. However, in absence of information most workers (67%) believe female managers are worse mentors. This belief-driven discrimination is equivalent to 1.6% of wages and offsets their preferences in absence of information. These beliefs prior to mentor-mentee matches are particularly consequential given our finding that workers value mentorship highly, willing to forgo 5.65% of wages for a one-standard-deviation improvement in mentorship quality. These beliefs are primarily driven by the perception that female managers are less competent, and that competence is a key factor in mentorship effectiveness. A large body of evidence finds no gender gap in mentorship, leadership and competence suggesting that these beliefs are likely biased. While this literature has focused on documenting mentoring effectiveness after matches form, we are the first to identify the distribution of pre-match beliefs that may prevent optimal matches.

The economic magnitudes are substantial—workers would sacrifice 5.65% of wages for better mentoring, yet 67% believe female managers provide worse mentoring worth -1.6% of wages—and inform policy implications. Information interventions making manager quality transparent could improve worker-firm matches. Our heterogeneity results suggest that such interventions would be most effective when targeted at workers without advanced degrees and those from households with traditional educational hierarchies, as these groups are most likely to hold potentially biased beliefs about female mentorship ability. Furthermore, such policies can also reduce gender gap at managerial levels even in discriminatory firms operating in monopsonistic labor markets.

As labor markets increasingly recognize the value of mentorship with firms investing millions in mentoring initiatives while struggling to break glass ceilings at the same time, understanding how beliefs on gender gap in mentorship shape sorting decisions of workers is essential for designing effective policies to reduce disparities and improve match efficiency. Our paper provides the first systematic evidence on these beliefs. Beyond the specific application to gender gap in mentorship, our framework provides a general approach for separately identifying beliefs from preferences wherever information frictions affect economic decisions.

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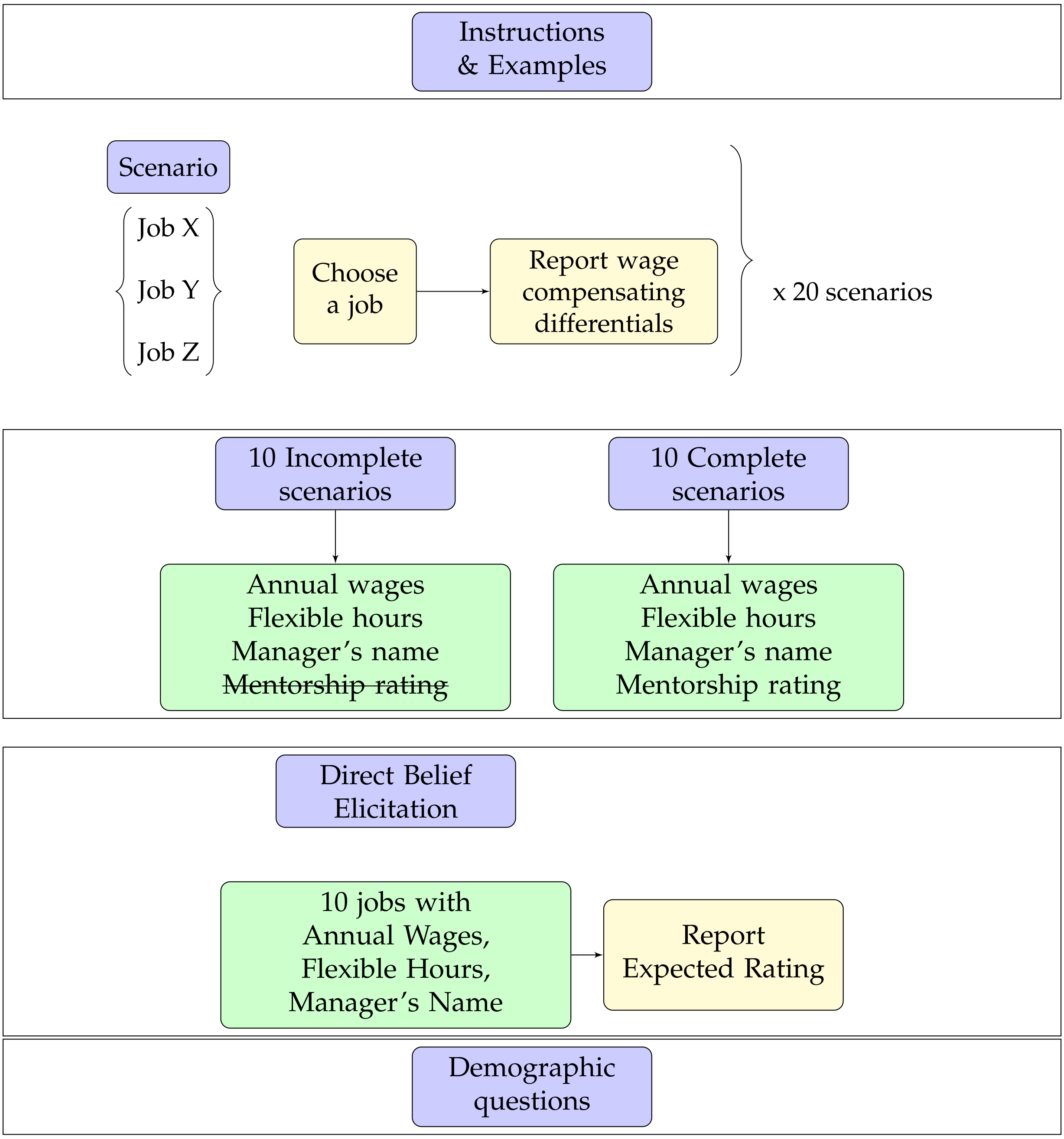
Tables and Figures

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.

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

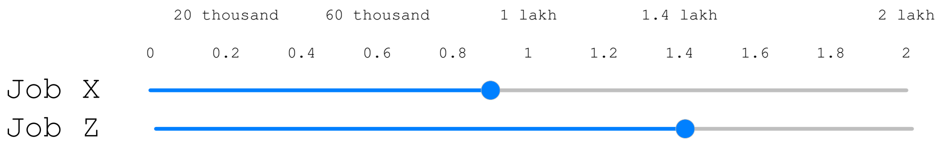
Job Y

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

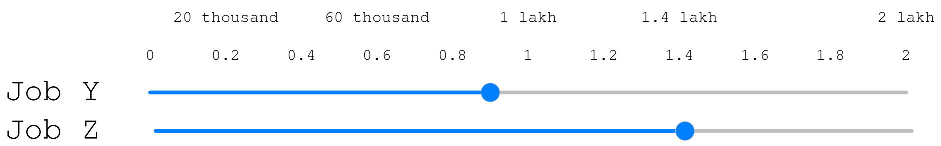
Job Y

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 across managers and scenarios

Panel A: 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

Panel B: 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]	

Panel C: Job attributes across male and female managers by scenario type

Incomplete scenarios

Attribute	Male Manager	Female Manager	Difference	p-value
Flexible hours	0.600	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]	

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: Panel A shows summary statistics of job attributes in the 60 jobs shown to respondents (3 jobs per scenario across 10 incomplete and 10 complete scenarios). The mentorship rating statistics come from the last 30 jobs because they are only shown in the 10 complete scenarios. Panel B shows the balance of job attributes by manager gender across all scenarios. Panel C shows the balance separately for incomplete and complete scenarios. Numbers in parentheses contain standard deviations and numbers in square brackets contain standard errors.

Table 4: Sample demographics

	Gender		
	Male	Female	Total
580 respondents	58.3	41.7	100
Area of Study:			
Arts	25.1	71.9	44.7
Engineering	49.4	10.7	33.3
Science	25.4	17.4	22.1
Family Income:			
Less than 2 lakhs (Less than $9,492)	37.6	24.4	32.1
2 lakhs to 5 lakhs ($9,492 to $23,730)	26.9	24.0	25.7
5 lakhs to 10 lakhs ($23,730 to $47,460)	21.3	30.2	25.0
10 to 20 lakhs ($47,460 to $94,921)	11.5	15.3	13.1
Above 20 lakhs (Above $94,921)	2.7	6.2	4.1
Mother's Education:			
Below High School	17.8	11.2	15.0
High School	32.8	18.6	26.9
Bachelor's	38.5	46.3	41.7
Master's	8.0	16.9	11.7
Above Master's	3.0	7.0	4.7
Father's Education:			
Below High School	9.2	7.4	8.4
High School	21.3	11.2	17.1
Bachelor's	51.5	55.4	53.1
Master's	13.9	17.8	15.5
Above Master's	4.1	8.3	5.9
Mother's Occupation:			
Government	10.9	15.3	12.8
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 5: Job choices and compensating differentials by manager gender and scenario type

Panel A: Percentages of chosen jobs with male and female managers

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

Panel B: Average compensating differentials for unchosen jobs

	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)	

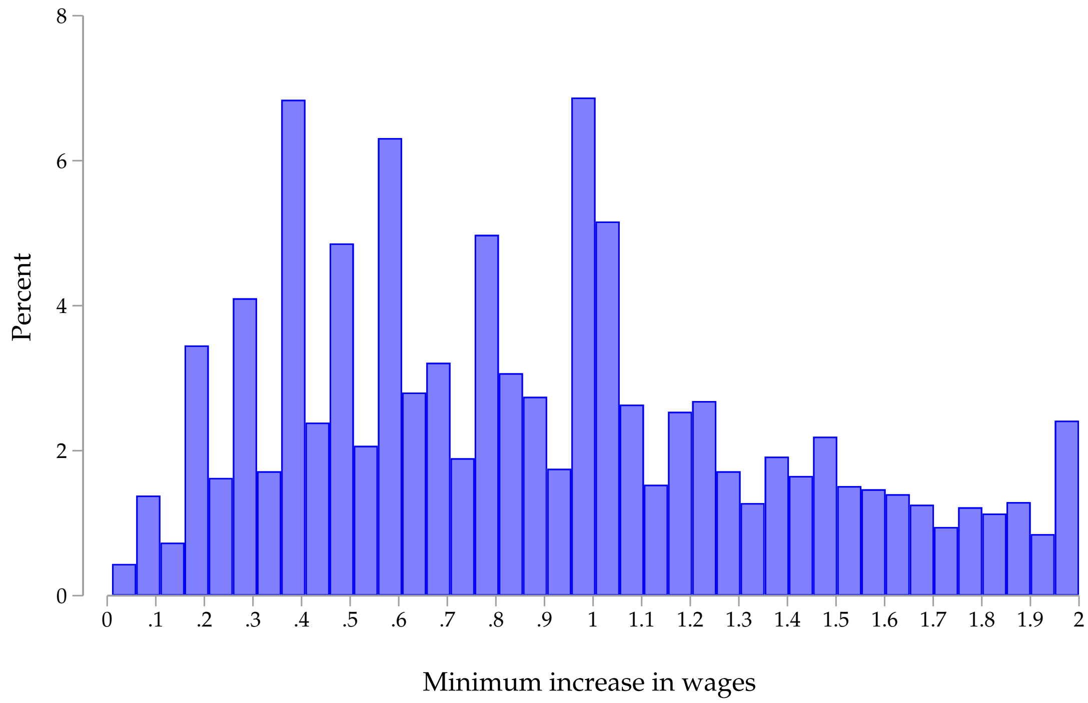
Notes: Panel A shows the percent of jobs chosen with male and female managers in the incomplete scenarios (where mentorship rating was not shown to respondents) and in the complete scenarios (where mentorship rating was shown). Percentages are shown for all respondents and disaggregated by respondent gender. Panel B shows average compensating differentials demanded by respondents for unchosen jobs, in units of 1 lakh (hundred thousand) INR. Standard deviations in parentheses, standard errors for differences in parentheses. *** denotes statistical significance at the 1% level.

Table 6: 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 2: 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 7: Preference and Belief Parameter Estimates

Panel A: 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	0.1%	β_i^G (Male Manager)	-0.119***	1.7%
	(0.012)			(0.019)	
$\tilde{\beta}_i^H = \beta_i^H + \beta_i^R \alpha_i^H$	1.134***	16.2%	β_i^H (Flexible Hours)	0.777***	11.1%
	(0.059)			(0.027)	
$\tilde{\beta}_i^W = \beta_i^W + \beta_i^R \alpha_i^W$	1.369***	19.6%	β_i^W (Annual Wages)	1	
	(0.068)				
			β_i^R (Mentorship)	0.792***	11.3%
				(0.030)	
Observations	11,600			11,600	

Panel B: Belief Parameters

Belief Parameter		Valuation of Beliefs		
	Estimate		in 10^5 INR	% of wages
α_i^G (Male managers)	0.142***	$\beta_i^R \alpha_i^G$ (Male managers)	0.112***	1.6%
	(0.029)		(0.023)	

Notes: Panel A shows estimates from estimating equation system (16) for each individual and reports the averages $E(\tilde{\beta}_i^x)$ for each attribute $x \in \{G, H, W\}$ in the incomplete scenarios and $E(\beta_i^x)$ for each attribute $x \in \{G, H, R\}$ in the complete scenarios. β_i^W is normalized to 1. Panel B shows belief parameters where $\alpha_i^G = \frac{\tilde{\beta}_i^G - \beta_i^G}{\beta_i^R}$ and the valuation of beliefs $\beta_i^R \alpha_i^G = \tilde{\beta}_i^G - \beta_i^G$. 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 block bootstrap at the individual level with 1,000 replications. 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).

Table 8: Heterogeneity in Parameters by LASSO-selected demographics

	(1) Beliefs	(2) Preferences
Father's × Mother's education		
Master's × Above Master's	-0.116*	
	(0.064)	
Own education		
Mphil/PhD	-0.101**	
	(0.045)	
1(Father employed)=0	-0.038**	
	(0.016)	
Constant	0.074***	-0.076***
	(0.006)	(0.005)
Observations	580	580
R-squared	0.023	0.000

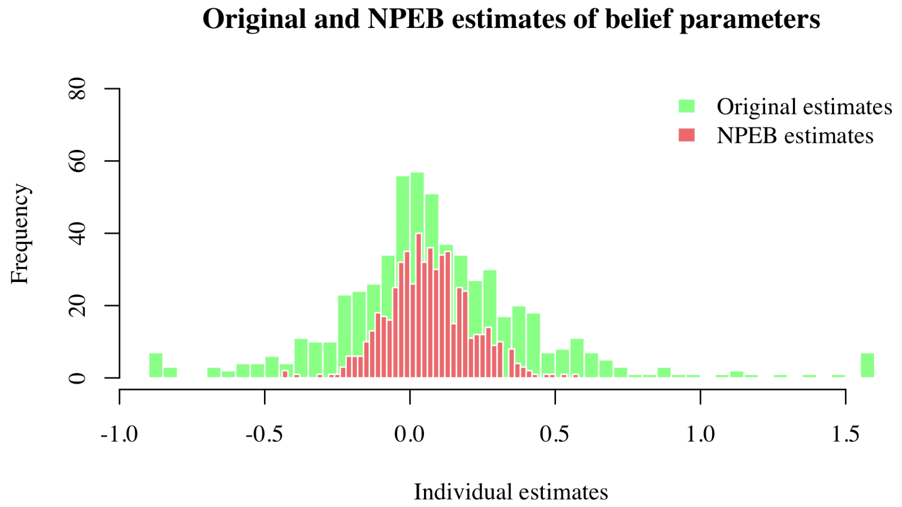
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Outcome variables are estimates obtained after shrinking individual-level structural parameter estimates on preferences and beliefs using a non-paramteric empirical Bayes procedure. The preference parameter captures willingness to forgo wages to work for male managers. The belief parameter captures beliefs about male managers' mentorship ability relative to female managers. Demographic variables are selected using LASSO (Least Absolute Shrinkage and Selection Operator) with 10-fold cross-validation from a set of demographic covariates including gender, field of study, education level, family income, parental education, parental employment, and interactions of parental demographics. The penalty parameter λ was chosen from a grid of 100 values to minimize mean squared error.

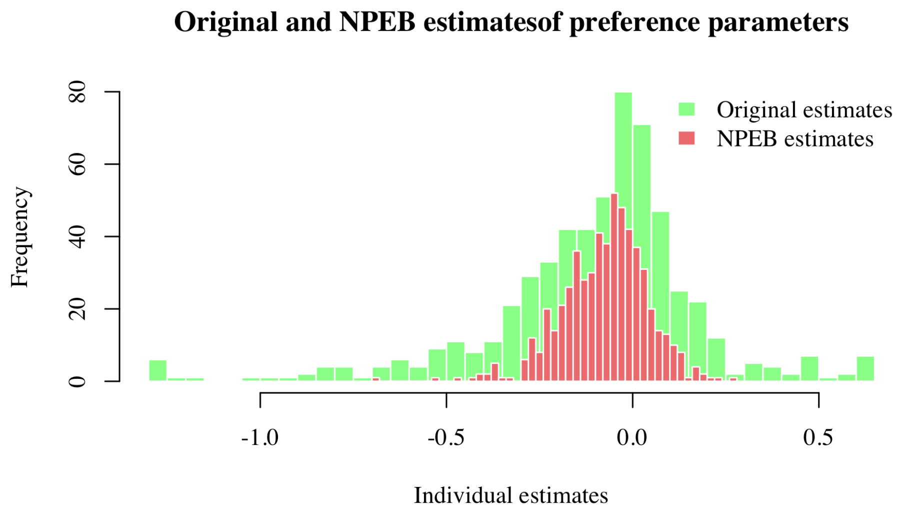
Figure 3: Distribution of Individual Raw Estimates and NPEB Estimates

(a) Beliefs on Male relative to Female Managers' Mentorship



Notes: The figure plots the histograms of the original individual estimates of the valuation of beliefs about male managers' mentorship ability relative to female managers (winsorized at the 1st and 99th percentiles), and overlays the corresponding non-parameteric empirical Bayes (NPEB) estimates.

(b) Preferences on Male relative to Female Managers



Notes: The figure plots the histograms of the original individual estimates of the preference for male managers relative to female managers (winsorized at the 1st and 99th percentiles), and overlays the corresponding non-parameteric empirical Bayes (NPEB) estimates.

A Appendix: 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.

B Appendix: Non-identification with choice probabilities

Consider 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 $\epsilon_i \equiv \{\epsilon_{i1}, \ldots, \epsilon_{iJ}\}$ has the interpretation of resolvable uncertainty as in Blass et al. (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.

B.1 Non-identification with choice probabilities with additional parametric assumptions

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.[35] 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

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

[35]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.

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.

C Appendix: Incorporating other managerial qualities in the model

Let $i = 1, \ldots, N$ index individuals. Each individual i, for each managerial quality (other than mentorship) indexed by $q = 1, \ldots, Q$, provides a single ordinal statement $Y_{iq} \in \{-1, 0, +1\}$ about whether they perceive a male manager to be better, similar, or worse than a female manager in the q^{th} quality Q_q. Hence, for individual i, the observed perception data are $\left\{(Y_{iq})_{q=1,\ldots,Q}\right\} \in \{-1, 0, +1\}^Q$.

A consequent question that arises is whether the negative beliefs about female manager mentorship that we document are robust conditional on other managerial qualities. To this end, the parameter of interest can be represented as the difference in expected mentorship quality between female and male managers conditional on other managerial qualities $\mathbb{Q} \equiv \{Q_1, \ldots, Q_K\} \in \mathbb{R}^K$ while supressing other job attributes to reduce notational clutter:

$$E[R_j \mid G_j = F, \mathbb{Q}] - E[R_j \mid G_j = M, \mathbb{Q}] \tag{C.1}$$

C.1 Utility function

The utility of individual i from job j is given by:

$$U_{ij} = X_j'\beta_i + \sum_{q=1}^{Q} \beta_i^q Q_{iq}^{g(j)} + \epsilon_{ij} \tag{C.2}$$

where $X_j \equiv (G_j, W_j, R_j, H_j)'$ is the vector of observable attributes of job j, $Q_{iq}^{g(j)}$ is the perceived latent quality of the manager of job j for individual i. The preference parameters of individual i is given by the vector:

$$\beta_i \cup \{\beta_i^q\}_{q=1}^{Q} \equiv \left(\beta_i^G, \beta_i^W, \beta_i^H, \beta_i^R\right)' \cup \left(\{\beta_i^q\}_{q=1}^{Q}\right)' \in \mathbb{R}^{K+1+Q}$$

C.2 Latent Quality

Let individual i's perception of the q^{th} latent quality of manager of gender $g \in \{M, F\}$ be denoted by Q_{iq}^g. We model the latent qualities Q_{iq}^g as:

$$Q_{iq}^g = \mu_q + \delta_q \mathbb{1}(g = M) + \nu_{iq}^g \qquad \nu_{iq}^g \sim \mathcal{N}(0, \sigma_q^{g^2}), \tag{C.3}$$

where, δ_q captures average beliefs that male managers exceed female managers in quality q, $(\nu_{iq}^M, \nu_{iq}^F)' \sim \mathcal{N}\left(0, \Sigma_q\right)$, Σ_q is the covariance matrix capturing the correlations between the errors across different qualities given by:

$$\Sigma_q = \begin{pmatrix} \sigma_q^{M^2} & \rho_k \sigma_q^{MF} \\ \rho_k \sigma_q^{MF} & \sigma_q^{F^2} \end{pmatrix}$$

Denote $D_{iq} \equiv Q_{iq}^M - Q_{iq}^F$, the difference in i's perceptions of the q^{th} quality between male and female managers, and $\eta_{iq} \equiv (\nu_{iq}^M - \nu_{iq}^F)$. Then given the parametrization of the latent qualities we have:

$$D_{iq} \equiv Q_{iq}^M - Q_{iq}^F = \delta_q + \eta_{iq} \tag{C.4}$$

Thus, for each individual i and quality q, we can represent their perception data as:

$$Y_{iq} = \begin{cases} +1 & \text{if } D_{iq} > \overline{\tau_q}, \\ 0 & \text{if } D_{iq} \in [-\underline{\tau_q}, \overline{\tau_q}], \\ -1 & \text{if } D_{iq} < -\underline{\tau_q} \end{cases} \tag{C.5}$$

where $\overline{\tau_q}$ and $\underline{\tau_q}$ are thresholds that partition the q^{th} continuous latent quality difference into three categories observed in the data. Given distributional assumptions, we have $D_{iq} \sim \mathcal{N}\left(\delta_q, \quad \sigma_{D_q}^2\right)$, where $\sigma_{D_q}^2 \equiv \sigma_q^{M^2} + \sigma_q^{F^2} - 2\rho_q \sigma_q^{MF}$.

C.3 Identification

Given the setup and distributional assumptions this leads us to an ordered probit model. The shares of individuals with perceptions $Y_{iq} = +1, 0, -1$ can be expressed as:

$$P(Y_{iq} = +1) = P(D_{iq} > \overline{\tau_q}) = 1 - \Phi\left(\frac{\overline{\tau_q} - \delta_q}{\sigma_{D_q}}\right)$$
$$P(Y_{iq} = 0) = P(-\underline{\tau_q} \leq D_{iq} \leq \overline{\tau_q}) = \Phi\left(\frac{\overline{\tau_q} - \delta_q}{\sigma_{D_q}}\right) - \Phi\left(\frac{-\underline{\tau_q} - \delta_q}{\sigma_{D_q}}\right)$$
$$P(Y_{iq} = -1) = P(D_{iq} < -\underline{\tau_q}) = \Phi\left(\frac{-\underline{\tau_q} - \delta_q}{\sigma_{D_q}}\right)$$

We have a system of two linearly independent equations with four parameters $\Theta_q \equiv \{-\delta_q, \sigma_{D_q}, \overline{\tau_q}, \underline{\tau_q}\}$ for each quality q. We normalize one of the thresholds, $\underline{\tau_q}$, to zero and the variance $\sigma_{D_q}^2$ to 1. This gives us two equations in two unknowns for each quality q:

$$P(Y_{iq} = +1) = 1 - \Phi\left(\overline{\tau_q} - \delta_q\right)$$
$$P(Y_{iq} = -1) = \Phi(-\delta_q)$$

Consequently, the empirical shares of perceptions point identify the parameters $\{\delta_q, \overline{\tau_q}\}$ for each quality q.

C.3.1 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 and their perceptions in the complete scenarios is given by

$$\mathbb{E}_i\left[U_{ij} \mid X_j, \mathbb{Q}\right] = X_j'\beta_i + \sum_{q=1}^{Q} \beta_i^q Q_{iq}^{g(j)} + \mathbb{E}_i\left(\epsilon_{ij} \mid X_j\right)$$

Each individual i knows their preferences and perceptions and hence do not take expectations over them. Note that given our model of latent qualities, we can express $Q_{iq}^{g(j)}$ as:

$$\begin{aligned}
Q_{iq}^{g(j)} &= \mu_q + \delta_q \mathbb{1}(g(j) = M) + \nu_{iq}^{g(j)} \\
&= \mu_q + \delta_q G_j + \nu_{iq}^{g(j)} \\
&= \mu_q + \delta_q G_j + \nu_{iq}^{M} G_j + \nu_{iq}^{F}(1 - G_j) \\
&= \mu_q + \left(\delta_q + \eta_{iq}\right) G_j + \nu_{iq}^{F}
\end{aligned}$$

Substituting $Q_{iq}^{g(j)} = \mu_q + \left(\delta_q + \eta_{iq}\right) G_j + \nu_{iq}^{F}$, we can express the expected utility as:

$$\begin{aligned}
\mathbb{E}_i\left[U_{ij} \mid X_j, \mathbb{Q}\right] &= X_j'\beta_i + \sum_{q=1}^{Q} \beta_i^q \left(\mu_q + \left(\delta_q + \eta_{iq}\right) G_j + \nu_{iq}^{F}\right) + \mathbb{E}_i\left(\epsilon_{ij} \mid X_j\right) \\
&= X_j'\beta_i + \sum_{q=1}^{Q} \beta_i^q \mu_q + \sum_{q=1}^{Q} \beta_i^q (\delta_q + \eta_{iq}) G_j + \sum_{q=1}^{Q} \beta_i^q \nu_{iq}^{F} + \mathbb{E}_i\left(\epsilon_{ij} \mid X_j\right) \\
&= \theta_i + X_j'\beta_i + \left(\sum_{q=1}^{Q} \beta_i^q (\delta_q + \eta_{iq})\right) G_j + \mathbb{E}_i\left(\epsilon_{ij} \mid X_j\right)
\end{aligned}$$

where $\theta_i \equiv \sum_{q=1}^{Q} \beta_i^q \mu_q + \sum_{q=1}^{Q} \beta_i^q \nu_{iq}^{F}$ is a constant term for individual i. Expanding $X_j = (G_j, W_j, R_j, H_j)'$, we can express the expected utility as:

$$
\begin{aligned}
\mathbb{E}_i\left[U_{ij} \mid X_j, \mathbb{Q}\right] &= \theta_i + \beta_i^G G_j + \beta_i^W W_j + \beta_i^R R_j + \beta_i^H H_j + \left(\sum_{q=1}^{Q} \beta_i^q(\delta_q + \eta_{iq})\right) G_j + \mathbb{E}_i\left(\epsilon_{ij} \mid X_j\right) \\
&= \theta_i + \left(\beta_i^G + \sum_{q=1}^{Q} \beta_i^q(\delta_q + \eta_{iq})\right) G_j + \beta_i^W W_j + \beta_i^R R_j + \beta_i^H H_j + \mathbb{E}_i\left(\epsilon_{ij} \mid X_j\right) \\
&= \theta_i + \left(\beta_i^G + \sum_{q=1}^{Q} \beta_i^q \delta_q\right) G_j + \sum_{q=1}^{Q} \beta_i^q \eta_{iq} G_j + \beta_i^W W_j + \beta_i^R R_j + \beta_i^H H_j + \mathbb{E}_i\left(\epsilon_{ij} \mid X_j\right)
\end{aligned}
$$

Note that δ_q is identified from the perception data as described in the previous section. However, η_{iq} is unknown. We estimate η_{iq} for each i and for all q with its expectation conditional on individual i's perception data of the q^{th} quality. Using properties of truncated normal distributions, for each quality q we have:

$$
\widehat{\eta_{iq}} = E[\eta_{iq} \mid Y_{iq}] = \begin{cases}
E[\eta_{iq} \mid Y_{iq} = +1] = E[\eta_{iq} \mid \eta_{iq} > \overline{\tau_q} - \delta_q] & = \frac{\phi(\widehat{\overline{\tau_q}} - \widehat{\delta_q})}{1 - \Phi(\widehat{\overline{\tau_q}} - \widehat{\delta_q})} \\[2em]
E[\eta_{iq} \mid Y_{iq} = 0] = E[\eta_{iq} \mid -\delta_q \leq \eta_{iq} \leq \overline{\tau_q} - \delta_q] & = \frac{\phi(-\widehat{\delta_q}) - \phi(\widehat{\overline{\tau_q}} - \widehat{\delta_q})}{\Phi(\widehat{\overline{\tau_q}} - \widehat{\delta_q}) - \Phi(-\widehat{\delta_q})} \\[2em]
E[\eta_{iq} \mid Y_{iq} = -1] = E[\eta_{iq} \mid \eta_{iq} < -\delta_q] & = -\frac{\phi(-\widehat{\delta_q})}{\Phi(-\widehat{\delta_q})}
\end{cases}
$$

where $\widehat{\delta_q}$ and $\widehat{\overline{\tau_q}}$ are estimated from the first-step ordered probit model for latent managerialqualities.

Thus expressing the expected utility in terms of the estimated η_{iq}, we have:

$$
\mathbb{E}_i\left[U_{ij} \mid X_j, \mathbb{Q}\right] = \theta_i + \left(\beta_i^G + \sum_{q=1}^{Q} \beta_i^q \delta_q\right) G_j + \sum_{q=1}^{Q} \beta_i^q \widehat{\eta_{iq}} G_j + \beta_i^W W_j + \beta_i^R R_j + \beta_i^H H_j + \mathbb{E}_i\left(\epsilon_{ij} \mid X_j\right)
$$

Maintaining assumptions (1) and (2) described in section 5, the difference in expected utility between jobs j and k for individual i given the reported compensating differentials Δ_{ijk} is given by:

$$
\begin{aligned}
\Delta_{ijk} = &\left(\beta_i^G + \sum_{q=1}^{Q} \beta_i^q \delta_q\right)(G_j - G_k) + \sum_{q=1}^{Q} \beta_i^q \left[\widehat{\eta_{iq}}(G_j - G_k)\right] \\
&+ \beta_i^W (W_j - W_k) + \beta_i^R (R_j - R_k) + \beta_i^H (H_j - H_k)
\end{aligned} \tag{C.6}
$$

This identifies the parameters: $\left\{\left\{\beta_i^G + \sum_{q=1}^{Q} \beta_i^q \delta_q\right\}_{q=1}^{Q}, \left\{\beta_i^q\right\}_{q=1}^{Q}, \beta_i^R, \beta_i^H\right\}$ for each individual i. Given that $\{\delta_q\}_{q=1}^{Q}$ is identified from the perception data, we can separately identify the parameters $\{\beta_i^G\}$ for each individual i.

C.3.2 Incomplete scenarios

In the incomplete scenarios, individuals do not observe R_j and hence take expectations over it while computing their expected utility from job j in the incomplete scenarios. We model the mentorship quality R_j in terms of the attributes of job j and individual i's perceived latent qualities $Q_{iq}^{g(j)}$ of the manager of gender $g(j) \in \{M, F\}$ as follows (suppressing other job attributes to reduce notational clutter):

$$R_j = \alpha_i^G G_j + \sum_{q=1}^{Q} \alpha_i^q Q_{iq}^{g(j)} + u_{ij} \tag{C.7}$$

where $E\left[u_{ij} \mid G_j, \left\{Q_{iq}^{g(j)}\right\}_q\right] = 0$ for all i, j, q.

Replacing this in the expression for R_j, we have:

$$\begin{aligned}
R_j &= \alpha_i^G G_j + \sum_{q=1}^{Q} \alpha_i^q \left(\mu_q + \left(\delta_q + \eta_{iq}\right) G_j + \nu_{iq}^F\right) + u_{ij} \\
&= \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q (\delta_q + \eta_{iq})\right) G_j + \sum_{q=1}^{Q} \alpha_i^q \mu_q + \sum_{q=1}^{Q} \alpha_i^q \nu_{iq}^F + u_{ij} \\
&= \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q (\delta_q + \eta_{iq})\right) G_j + C_i + u_{ij}
\end{aligned}$$

where $C_i \equiv \sum_{q=1}^{Q} \alpha_i^q \mu_q + \sum_{q=1}^{Q} \alpha_i^q \nu_{iq}^F$ is constant for individual i. Subsequently,

$$\begin{aligned}
E_i[R_j \mid G_j, \mathbb{Q}] &= E_i\left[R_j \mid G_j, \left\{Q_{iq}^{g(j)}\right\}_q\right] \\
&= \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q (\delta_q + \eta_{iq})\right) G_j + C_i
\end{aligned}$$

Thus our parameter of interest can be expressed as:

$$E_i[R_j \mid G_j = M, \mathbb{Q}] - E_i[R_j \mid G_j = F, \mathbb{Q}] = \alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q (\delta_q + \eta_{iq}) \tag{C.8}$$

Expanding this to include other job attributes W_j and H_j, we have:

$$E_i[R_j \mid \widetilde{X_j}, \mathbb{Q}] = \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q (\delta_q + \eta_{iq})\right) G_j + C_i + \alpha_i^W W_j + \alpha_i^H H_j$$

where $\widetilde{X_j} \equiv (G_j, W_j, H_j)'$ is the vector of observable attributes in the incomplete scenarios.

The expected utility of individual i from job j in the incomplete scenarios is given by:

$$\begin{aligned}\mathbb{E}_i \left[U_{ij} \mid \widetilde{X_j}, \mathbb{Q}\right] = \theta_i + \left(\beta_i^G + \sum_{q=1}^{Q} \beta_i^q \delta_q\right) G_j + \sum_{q=1}^{Q} \beta_i^q \widehat{\eta_{iq}} G_j + \beta_i^W W_j + \beta_i^H H_j \\ + \beta_i^R \mathbb{E}_i[R_j \mid \widetilde{X_j}, \mathbb{Q}] + \mathbb{E}_i \left(\epsilon_{ij} \mid \widetilde{X_j}, \mathbb{Q}\right)\end{aligned}$$

Substituting the expression for $E_i[R_j \mid \widetilde{X_j}, \mathbb{Q}]$, we have:

$$\begin{aligned}\mathbb{E}_i \left[U_{ij} \mid \widetilde{X_j}, \mathbb{Q}\right] &= \theta_i + \left(\beta_i^G + \sum_{q=1}^{Q} \beta_i^q \delta_q\right) G_j + \sum_{q=1}^{Q} \beta_i^q \widehat{\eta_{iq}} G_j + \beta_i^W W_j + \beta_i^H H_j \\ &\quad + \beta_i^R \left(\left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q (\delta_q + \widehat{\eta_{iq}})\right) G_j + C_i + \alpha_i^W W_j + \alpha_i^H H_j\right) + \mathbb{E}_i \left(\epsilon_{ij} \mid \widetilde{X_j}, \mathbb{Q}\right) \\ &= \theta_i + \left(\beta_i^G + \sum_{q=1}^{Q} \beta_i^q \delta_q\right) G_j + \sum_{q=1}^{Q} \beta_i^q \widehat{\eta_{iq}} G_j + \beta_i^W W_j + \beta_i^H H_j \\ &\quad + \beta_i^R \left(\left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q \delta_q)\right) G_j + \sum_{q=1}^{Q} \alpha_i^q \widehat{\eta_{iq}} G_j + C_i + \alpha_i^W W_j + \alpha_i^H H_j\right) \\ &\quad + \mathbb{E}_i \left(\epsilon_{ij} \mid \widetilde{X_j}, \mathbb{Q}\right)\end{aligned}$$

This can be simplified to:

$$\begin{aligned}\mathbb{E}_i \left[U_{ij} \mid \widetilde{X_j}, \mathbb{Q}\right] = \theta_i + \beta_i^R C_i + \left(\beta_i^G + \sum_{q=1}^{Q} \beta_i^q \delta_q + \beta_i^R \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q \delta_q\right)\right) G_j + \sum_{q=1}^{Q} (\beta_i^q + \beta_i^R \alpha_i^q) \widehat{\eta_{iq}} G_j \\ + (\beta_i^W + \beta_i^R \alpha_i^W) W_j + (\beta_i^H + \beta_i^R \alpha_i^H) H_j + \mathbb{E}_i \left(\epsilon_{ij} \mid \widetilde{X_j}, \mathbb{Q}\right)\end{aligned}$$

Using reported compensating differentials $\widetilde{\Delta}_{ijk}$, and imposing assumptions (1) and (2) now conditional on perceptions, we can express the difference in expected utility between jobs j and k for individual i in the incomplete scenarios as:

$$\widetilde{\Delta}_{ijk} = \left(\beta_i^G + \sum_{q=1}^{Q} \beta_i^q \delta_q + \beta_i^R \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q \delta_q\right)\right)(G_j - G_k) + \sum_{q=1}^{Q} (\beta_i^q + \beta_i^R \alpha_i^q)\widehat{\eta_{iq}}(G_j - G_k)$$
$$+ (\beta_i^W + \beta_i^R \alpha_i^W)(W_j - W_k) + (\beta_i^H + \beta_i^R \alpha_i^H)(H_j - H_k) \tag{C.9}$$

This for each individual i, identifies the parameters :

$$\left\{ \left\{ \beta_i^G + \sum_{q=1}^{Q} \beta_i^q \delta_q + \beta_i^R \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q \delta_q\right) \right\}_{q=1}^{Q}, \left\{\beta_i^q + \beta_i^R \alpha_i^q\right\}_{q=1}^{Q}, \beta_i^W + \beta_i^R \alpha_i^W, \beta_i^H + \beta_i^R \alpha_i^H \right\}$$

Given that $\{\delta_q\}_{q=1}^{Q}$ is identified from the perception data, and the variation in compesating differentials in the complete scenarios identify the parameters $\left\{\beta_i^G, \beta_i^H, \beta_i^R, \{\beta_i^q\}_{q=1}^{Q}\right\}$ for each individual i, the variation between the incomplete and the complete scenarios separately identify the parameters $\left\{\alpha_i^G, \alpha_i^W, \alpha_i^H, \alpha_i^R, \{\alpha_i^q\}_{q=1}^{Q}\right\}$ for each individual i.

Thus our parameter of interest of the beliefs on the gender gap in mentorship conditional on other managerial qualities $\mathbb{Q}$ is identified by:

$$E_i[R_j \mid G_j = F, \mathbb{Q}] - E_i[R_j \mid G_j = M, \mathbb{Q}] = \alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q (\delta_q + \eta_{iq})$$

The valuation of this parameter of interest is simply:

$$\beta_i^R \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q (\delta_q + \eta_{iq})\right)$$

Further, it is important to note that the average of the individual-specific parameter of interest across all individuals i is equal to

$$\frac{1}{N}\sum_{i=1}^{N} \beta_i^R \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q (\delta_q + \eta_{iq})\right)$$
$$= \frac{1}{N}\sum_{i=1}^{N} \beta_i^R \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q \delta_q\right) + \frac{1}{N}\sum_{i=1}^{N} \beta_i^R \left(\sum_{q=1}^{Q} \alpha_i^q \eta_{iq}\right)$$

Note that the second term $\frac{1}{N}\sum_{i=1}^{N}\left(\sum_{q=1}^{Q} \alpha_i^q \eta_{iq}\right)$ goes to zero as $N \to \infty$, since η_{iq} is the difference in the latent qualities and follows a symmetric distribution around zero. Thus, the average of the parameter of interest across all individuals i boils down to:

$$\beta_i^R \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q \delta_q \right)$$

The beliefs on the gender gap in mentorship conditional on other managerial qualities can be can be decomposed into two components. The first component is trait-driven, $\frac{\beta_i^R \sum_{q=1}^{Q} \alpha_i^q \delta_q}{\beta_i^R \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q \delta_q \right)}$ reflecting the share of beliefs on the gender gap in mentorship driven by perceived gender gap in traits. The second component reflects the residual share in beliefs conditional on gender, $\frac{\beta_i^R \alpha_i^G}{\beta_i^R \left(\alpha_i^G + \sum_{q=1}^{Q} \alpha_i^q \delta_q \right)}$ reflecting respondents' belief about mentorship differences based on gender other than the considered traits.

C.4 Estimation and Inference

We implement a block-bootstrap procedure with 1,000 replications that resamples individuals and re-estimates all of the three following steps:

Step 1: We estimate gender differences in perceived managerial qualities $\{\delta_q\}$ using ordered probit models on the perception data $\{Y_{iq}\}$.

Step 2: Using the first-stage estimates, we compute the residuals $\widehat{\eta_{iq}} = E[\eta_{iq}|Y_{iq}]$ using properties of truncated normal distributions.

Step 3: We jointly estimate individual-specific preference and belief parameters by stacking the compensating differential equations from both complete (equation C.6) and incomplete scenarios (equation C.9) into a single system. We estimate this system via constrained least squares with $\beta_i^W = 1$ normalized similar to our main estimation.

Similar to our original estimation and inference approach detailed in Appendix Section D, we use the bootstrap distribution for both point estimates and inference. Our reported parameter estimates and their standard errors are the means and standard deviations of the bootstrap distribution respectively. This approach accounts for the multi-step estimation error, generated regressor problem and arbitrary within-individual correlation.

C.5 Results

We summarize the main results from incorporating other perceived managerial traits into the model.

Panel A of Table F shows that after accounting for beliefs about latent traits, workers still exhibit a preference for female managers in the complete scenarios ($\beta_i^G + \sum_q \beta_i^q \delta_q = -0.045$, significant at 1% level). Given estimates of $\beta_i^q \delta_q$ for all q we can estimate $\beta_i^G = -0.053$ (0.75% of wages) as the pure gender preferences. This magnitude in comparison to our baseline model ($\beta_i^{G(baseline)} = -0.119$) is lower by more than half. This result provides empirical support for the idea that once we make men and women more similar along more dimensions, reassuringly the "pure" preference for gender declines substantially. We discuss this more in the main text of our paper.

Panel B shows that the strongest perceived trait difference between male and female managers is in competence ($\delta_{q_1} = 0.96$), and this trait is also significantly weighted in how individuals infer mentorship ($\beta_i^R \alpha_i^{q_1} = 0.015$, significant at 10% level).

Most importantly, Panel C reports the beliefs on gender gap in mentorship conditional on other traits and how much of it is driven by perceived gender gap in other traits. The total valuation of beliefs on gender gap in mentorship once conditioned on other traits reduces to 0.6% of wages. Compared to our baseline estimates this represents a reduction of 62.5%. Our model provides a useful decomposition of this conditional beliefs on gender gap in mentorship. Of this, 44% is attributable to perception of gender gaps in other traits. Thus, a substantial portion of the beliefs on gender gap in mentorship, reflects how individuals link perceived traits to mentorship conditional on gender.

Our extended model thus provides an explanation and quantifies the source of beliefs on gender gaps in mentorship.

D Appendix: 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:

$$\begin{bmatrix} \mathbf{\Delta_{jk}} \\ \vdots \\ \widetilde{\mathbf{\Delta}}_{\mathbf{jk}} \\ \vdots \end{bmatrix} = \begin{bmatrix} \mathbf{X_j} - \mathbf{X_k} & \mathbf{0} \\ \vdots & \vdots \\ \mathbf{0} & \widetilde{\mathbf{X}}_{\mathbf{j}} - \widetilde{\mathbf{X}}_{\mathbf{k}} \\ \vdots & \vdots \end{bmatrix}' (\boldsymbol{\beta} \quad \widetilde{\boldsymbol{\beta}}) + \mathbf{e} \tag{D.1}$$

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:

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

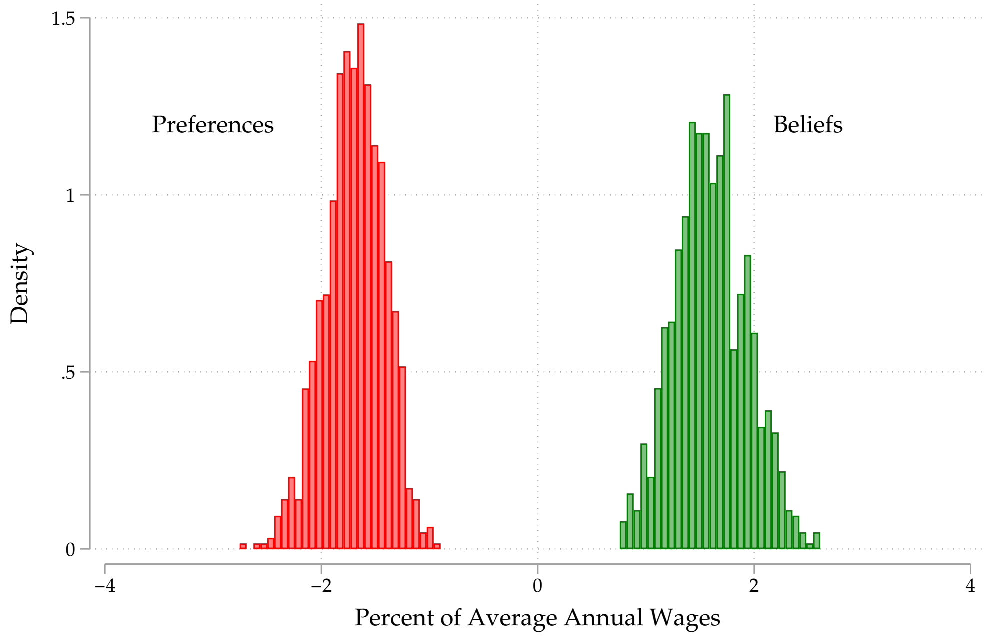
Preferences confounded with valuation of beliefs:

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

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 D.1: 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 D. These bootstrap distributions are used for estimation of means and standard errors of preferences and beliefs.

E Appendix: 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.

E.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,

$$\Delta_{ijk} = \sum_{x \in X} \beta_i^x (x_j - x_k) + \beta_i^{GR}(G_j R_j - G_k R_k) \tag{E.1}$$

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

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

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

$$\widetilde{\Delta}_{ijk} = \sum_{x \in \widetilde{X}} \left(\beta_i^x + \beta_i^R \alpha_i^x\right)(x_j - x_k) + \beta_i^{GR} \sum_{x \in \widetilde{X}} \alpha_i^x \left(x_j G_j - x_k G_k\right) \tag{E.2}$$

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 $\beta_i^G + \beta_i^{GR}\mathbb{E}_i(R_j)$.[36]

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 $\{\alpha_i^x\}_{x \in \widetilde{X}}$.[37]

[36] 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.

[37] 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

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

.

E.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

$$\Delta_{ijk} = \sum_{x \in X} \beta_i^x (x_j - x_k) \tag{E.3}$$

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

$$\widetilde{\Delta}_{ijk} = \sum_{x \in \widetilde{X}} \left(\beta_i^x + \beta_i^R \alpha_i^x \right) (x_j - x_k) + \beta_i^R \alpha_i^{GW} \left(G_j H_j - G_k H_k \right) \tag{E.4}$$

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'.

E.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

$$\frac{log(w_k + \Delta_{ijk})}{log(w_j)} = \beta_i^G(G_j - G_k) + \beta_i^H(H_j - H_k) + \beta_i^R(R_j - R_k) \tag{E.5}$$

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

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

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

$$\frac{log(w_k + \widetilde{\Delta}_{ijk})}{log(w_j)} = (\beta_i^G + \beta_i^R \alpha_i^G)(G_j - G_k) + (\beta_i^H + \beta_i^R \alpha_i^H)(H_j - H_k) + \beta_i^R \alpha_i^W \left(log(w_j) - log(w_k) \right) \tag{E.6}$$

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.

E.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 $\beta_i^R R_j$.[38]

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 $X_j \equiv \{G_j, W_j, H_j, f(R_j)\}$. 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.

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.

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

E.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:

$$U_{ij} = \sum_{x \in A} \beta_i^x x_j + \epsilon_{ij} \tag{E.7}$$

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:

$$\begin{aligned} \text{Incomplete Scenarios: } \mathbb{E}_i[U_{ij} \mid \tilde{X}_j] &= \sum_{x \in A \setminus Q} \beta_i^x x_j + \beta_i^Q \mathbb{E}_i(Q_j \mid \tilde{X}_j) + \mathbb{E}_i(\epsilon_{ij} \mid \tilde{X}_j) \\ \text{Complete Scenarios: } \mathbb{E}_i[U_{ij} \mid X_j] &= \sum_{x \in A \setminus Q} \beta_i^x x_j + \beta_i^Q \mathbb{E}_i(Q_j \mid X_j) + \mathbb{E}_i(\epsilon_{ij} \mid X_j) \end{aligned} \tag{E.8}$$

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:

$$\begin{aligned} \text{Complete Scenarios: } \mathbb{E}_i(Q_j \mid X_j) &= \sum_{x \in A \setminus Q} \gamma_i^x x_j + \gamma_i^R R_j + \mathbb{E}_i(\zeta_i \mid X_j) \\ \text{Incomplete Scenarios: } \mathbb{E}_i(Q_j \mid \tilde{X}_j) &= \sum_{x \in A \setminus Q} \gamma_i^x x_j + \gamma_i^R \mathbb{E}[R_j \mid \tilde{X}_j] + \mathbb{E}_i(\zeta_i \mid \tilde{X}_j) \\ &= \sum_{x \in A \setminus Q} \tilde{\gamma_i}^x x_j + \mathbb{E}_i(\zeta_i \mid \tilde{X}_j) \end{aligned} \tag{E.9}$$

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

$$\begin{aligned}
\text{Complete Scenarios: } \mathbb{E}_i[U_{ij} \mid X_j] &= \sum_{x \in A \setminus Q} (\beta_i^x + \beta_i^Q \gamma_i^x) x_j + \mathbb{E}_i(\epsilon_{ij} \mid X_j) \\
\text{Incomplete Scenarios: } \mathbb{E}_i[U_{ij} \mid \tilde{X}_j] &= \sum_{x \in A \setminus Q} (\beta_i^x + \beta_i^Q \tilde{\gamma}_i^x) x_j + \mathbb{E}_i(\epsilon_{ij} \mid \tilde{X}_j)
\end{aligned} \tag{E.10}$$

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

$$\begin{aligned}
\Delta_{ijk} &= \sum_{x \in A \setminus Q} \underbrace{(\beta_i^x + \beta_i^Q \gamma_i^x)}_{\beta_i^{x(CS)}} (x_j - x_k) \\
\tilde{\Delta}_{ijk} &= \sum_{x \in A \setminus Q} \underbrace{(\beta_i^x + \beta_i^Q \tilde{\gamma}_i^x)}_{\beta_i^{x(IS)}} (x_j - x_k)
\end{aligned} \tag{E.11}$$

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

$$\beta_i^{G(CS)} - \beta_i^{G(IS)} = \beta_i^Q (\gamma_i^G - \tilde{\gamma}_i^G) \tag{E.12}$$

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.

F Appendix Figures and Tables

Figure F.1: Survey definitions and instructions
(a) 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.

(b) 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.

Notes: Panel A shows the first part of the instructions that defined the job attributes used in the survey, and Panel B shows remaining instructions shown to respondents.

Table F.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

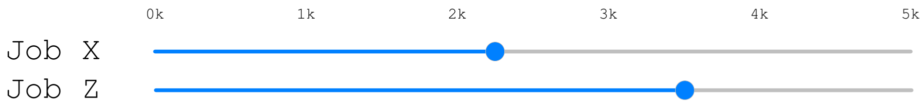
Job Y

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 F.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

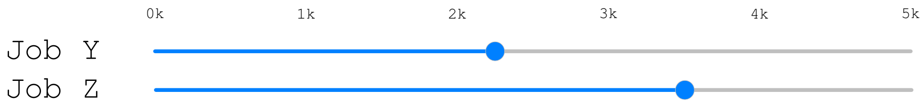
Job Y

Job Z

Compensating differential (*if job chosen was X*)

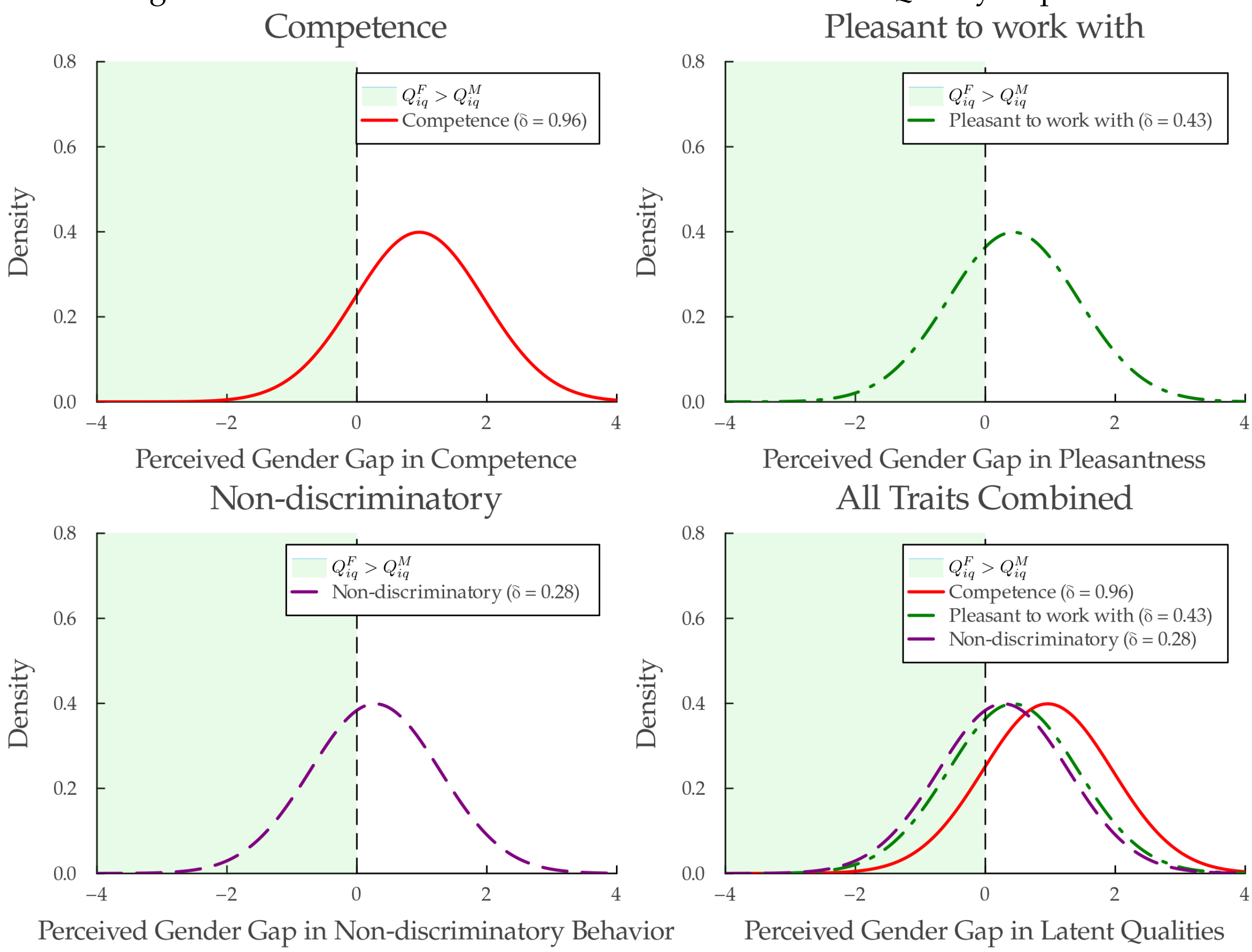
You chose Job X.
If you were to negotiate your wage, how much of a MINIMUM INCREASE IN WAGES would you need in each of the other jobs for you to choose it instead of Job X?
The scale here ranges from 0 to 5,000 USD.

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.

Figure F.2: Estimated Distributions of Perceived Latent Quality Gaps



Notes: Each panel shows the estimated distribution of perceived gender gaps in specific managerial qualities. The light green shaded region ($Q^F_{iq} > Q^M_{iq}$) represents the area where females are perceived to be strictly better than males. Distribution for trait q are estimated as Normal(δ_q, 1) where δ_q represents the mean perceived gap for trait q which in turn are estimated from the ordered probit models. The bottom-right panel overlays all three distributions for comparison.

Table F.3: Jointly Estimated Preference and Belief Parameter Estimates with Perception on other traits and Decomposition of beliefs

Panel A: Complete and Incomplete Scenarios:

Incomplete Scenarios			Complete Scenarios		
Parameters	in 10^5 INR	% of wages	Parameters	in 10^5 INR	% of wages
$\tilde{\beta}_i^{G,adj}$	-0.006	0.1%	$\beta_i^{G,adj}$	-0.045***	0.6%
	(0.005)		(Male Manager)	(0.007)	
$\tilde{\beta}_i^{H}$	1.134***	16.2%	β_i^{H} (Flexible Hours)	0.777***	11.1%
	(0.059)			(0.027)	
$\tilde{\beta}_i^{W}$	1.369***	19.6%	β_i^{W} (Annual Wages)	1	
	(0.068)				
			β_i^{R} (Mentorship)	0.792***	11.3%
				(0.030)	
Observations	11,600			11,600	

Panel B: Trait-Specific Components and δ Values

Parameters	Estimate	δ_q	Correlation b/w trait q and mentorship	Estimate
$\beta_i^{q_1}$	-0.009	0.958	$\beta_i^R \alpha_i^{q_1}$	0.015*
	(0.007)			(0.008)
$\beta_i^{q_2}$	0.002	0.280	$\beta_i^R \alpha_i^{q_2}$	0.004
	(0.004)			(0.005)
$\beta_i^{q_3}$	-0.001	0.428	$\beta_i^R \alpha_i^{q_3}$	0.004
	(0.003)			(0.004)

Panel C: Valuation of Belief Parameters and Decomposition

Parameter	Estimate	% of wages	Decomposition	
$\beta_i^R(\alpha_i^G + \sum_q \alpha_i^q \delta_q)$	0.039***	0.6%	Trait driven:	0.017*
	(0.009)			(0.008)
			Residual:	0.022***
				(0.009)
$\beta_i^R \alpha_i^H$	0.358***	5.1%		
	(0.044)			
$\beta_i^R \alpha_i^W$	0.369***	5.3%		
	(0.068)			

Notes: Panel A shows estimates from the jointly estimated model with trait adjustments. The complete scenario estimate for male managers includes trait-specific adjustments: $\beta_i^{G,adj} = \beta_i^G + \sum_{q=1}^3 \beta_i^q \delta_q$. The incomplete scenario parameter is $\tilde{\beta}_i^{G,adj} = \beta_i^G + \sum_q \beta_i^q \delta_q + \beta_i^R(\alpha_i^G + \sum_q \alpha_i^q \delta_q) + \sum_q(\beta_i^q + \beta_i^R \alpha_i^q)\eta_{iq}$. Panel B displays the trait-specific components where δ_q represents the average difference in trait q between male and female managers. Quality 1 (q_1) is competence, quality 2 (q_2) is non-discriminatory, and quality 3 (q_3) is pleasant to work with. Panel C shows belief parameters where the total valuation $\beta_i^R(\alpha_i^G + \sum_q \alpha_i^q \delta_q)$ is decomposed into residual $\beta_i^R \alpha_i^G$ and trait driven $\beta_i^R \sum_q \alpha_i^q \delta_q$, with trait driven explaining 44.0% of the gender gap. Standard errors are computed using block bootstrap at the individual level with 1,000 replications. Statistical significance at 1, 5, and 10% is denoted by ***, **, and *, respectively.

Figure F.3: Expected rating

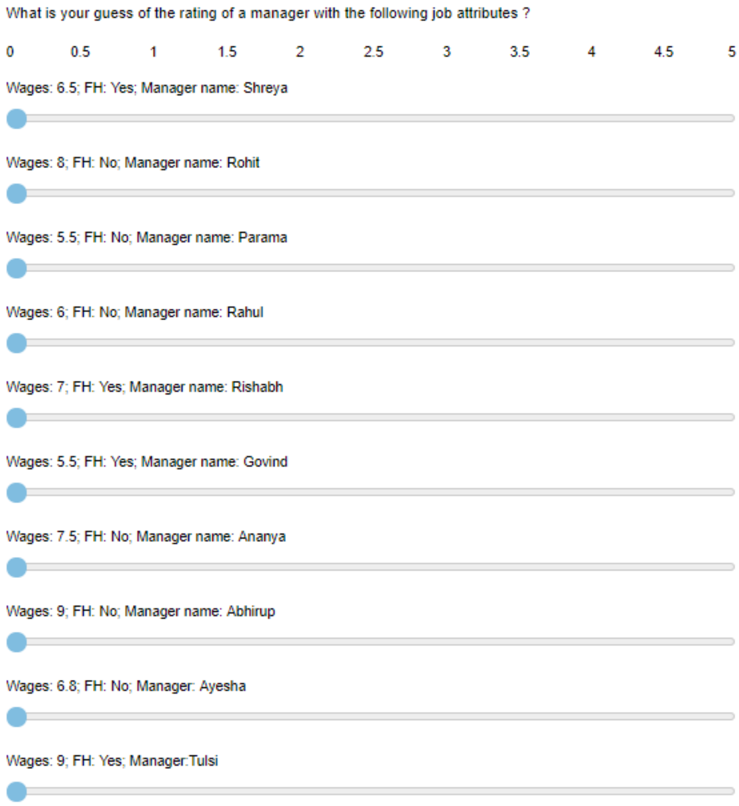


Table F.4: Estimates of expected beliefs from directly elicited belief data

	Directly Elicited Beliefs		
	All	Female	Male
Male Manager (α^G)	-0.042***	-0.027	-0.053**
	(0.012)	(0.016)	(0.016)
Flexible Hours (α^H)	0.321***	0.321***	0.321***
	(0.023)	(0.033)	(0.031)
Annual Wages (α^W)	0.278***	0.290***	0.270***
	(0.013)	(0.018)	(0.018)
Individual Fixed Effects	Yes	Yes	Yes
N	5,800	2,420	3,380
R^2	0.598	0.609	0.592

Notes: Standard errors are clustered at the individual level. These estimates are obtained from a fixed effects regression of directly elicited manager rating on the exogenously varied job attributes: indicator for male manager, flexibility of hours, and annual wages. Specifically, we estimate $R_{ij}^{direct} = \theta_i + \alpha^G G_j + \alpha^H H_j + \alpha^W W_j + \eta_{ij}$, where R_{ij}^{direct} is the directly elicited rating of manager in job j by individual i, G_j is an indicator of male manager, H_j is an indicator of flexible hours, and W_j is the annual wages of job j, and θ_i is an individual fixed effect.