Paternalistic Discrimination*

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We combine a simple model, two field experiments in Bangladesh and structural evidence to define and test for *paternalistic discrimination*, the preferential treatment of men over women to protect women from tasks perceived as unpleasant or harmful. We observe hiring and application decisions for a night-shift job that provides safe worker transport home at the end of the shift, an amenity that employers believe substantially reduces job costs for women. Keeping worker selection and productivity constant, we experimentally vary (i) whether employers know about the transport and (ii) worker payments. Not informing employers about the transport decreases demand for female labor by 22%—even when employers learn that workers receive a surprise cash payment large enough to purchase safe transport themselves. This suggests that employers discriminate paternalistically: They restrict women's employment choices to protect them from jobs that employers perceive as dangerous. Not informing applicants about the transport decreases female labor supply by 15%. We combine the results from both experiments in an equilibrium model and show that eliminating paternalistic discrimination reduces the simulated gender employment gap by 22% and increases female wages by 26%.

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1 Introduction

Economists traditionally distinguish between two forms of gender-based discrimination: *taste-based discrimination*, a preference for interacting with men over women (Becker, 1957), and *statistical discrimination*, a belief that men are more productive than women (Phelps, 1972; Arrow, 1973). However, a global norm to protect women (Glick et al., 2000) could be the source of another form of discrimination. Governments around the world restrict women's employment to protect them: 52 countries in hazardous work and 23 in night work (World Bank, 2023a).[1] This paper assesses whether protective gender norms may cause discrimination, that is, whether employers hire men over equally qualified and motivated women to protect women from physical injury, reputational damage, or long hours away from their families—potentially denying women opportunities to gain relevant skills and work experiences.

We combine a simple model, two field experiments, and structural estimates to define and test for *paternalistic discrimination: the preferential treatment of men to protect women from tasks perceived as unpleasant or harmful.* We augment a standard labor market model with other-regarding employers, i.e., employers who value their workers' welfare. We test the model's predictions using two labor market experiments in which we observe real hiring and application decisions for a night-shift job in Bangladesh and exogenously vary information about safe transport and wages. Finally, we estimate the model parameters and combine the results of both experiments to benchmark the importance of paternalistic discrimination and evaluate the effectiveness of transport and subsidy interventions.

The key innovation of our model is that the labor demand of other-regarding employers decreases in perceived worker job costs, such as danger. Building on traditional models of discrimination, our model incorporates distaste for interacting with a particular gender (taste-based discrimination), beliefs about the profitability of hiring from a particular gender (statistical discrimination), and beliefs about the welfare of a particular gender (other-regarding discrimination). We distinguish between two possible types of other-regarding discrimination, committed by either altruistic or paternalistic employers. Altruistic employers use *applicants' beliefs and preferences*, such as risk preferences, to calculate worker welfare, while paternalistic employers use *their own beliefs and preferences for workers* to calculate worker welfare. Our model yields five predictions, which we test in two field experiments and structural estimation.

We experimentally vary the perceived safety of a night-shift job to test the first theoretical prediction: Holding worker selection and productivity fixed, labor demand decreases in

[1] For example, women are barred from working during the night in some jobs in Nigeria and from working in mining and underground construction in Thailand (World Bank, 2023b; The Labour Protection Act B.E. 2541, 2014). Similar laws limit women's options in China, Argentina, the Republic of Korea, Cameroon, Saudi Arabia and other countries (US Department of State, 2022a,b; World Bank, 2023b). In South Asia, such laws are prevalent: Women in India face different restrictions than men when working at night, performing hazardous or difficult tasks (such as lifting heavy objects), and selling alcohol (Anand and Kaur, 2022). In addition, all but 17 countries ban women from fighting in combat (Fitriani et al., 2016).

perceived job costs for workers. We recruit 495 *employers*, individuals with recent hiring experience, in Dhaka, Bangladesh. These employers make 5,000 hiring decisions between one male and one female applicant (10 per employer) for a job created by the research team: a one-day workshop and office job on the night shift (7 p.m. to midnight). We randomly implement one hiring choice per employer and pay the employer based on the performance of the hired worker. We exogenously vary the perceived job costs by randomizing whether we inform employers that all workers receive free safe transport home at the end of the shift. To hold taste-based and statistical discrimination constant, we inform employers in the transport treatment that applicants do not know about the transport, only learn about it after the shift, and that there are no repeat shifts, that is, that information about the transport affects neither selection nor productivity. In addition, as every applicant is shown to several employers, we test whether information about the transport affects the hiring choices for the same woman, ruling out a myriad of confounds. We find that not informing employers about the transport reduces female hiring by 22% without changing taste-based or statistical discrimination.

We experimentally vary workers' and employers' pay to test the second theoretical prediction: Altruistic and paternalistic employers respond differently to providing workers with subsidies and transport. Altruistic employers demand workers weakly more when workers receive cash subsidies that allow them to choose whether to purchase safe transport than when workers receive safe transport directly. Paternalistic employers may demand workers less with subsidies than safe transport if they believe that workers *should* purchase the transport but, when given the choice, would not. We cross-randomize employers in the experiment into one of four subsidy treatments: (i) female workers receive a surprise subsidy of 1,000 Bangladesh Taka (BDT, or USD 10)—an amount much larger than the typical transport cost in our setting (Uber costs less than BDT 500 and is easily available and considered safe), (ii) male workers receive a surprise subsidy of BDT 1,000, (iii) employers receive a subsidy for hiring female workers of BDT 1,000, or (iv) neither employers nor workers receive a subsidy. We find that employers (i) report that women underestimate the costs of working at night and (ii) hire women significantly less with the female worker subsidy than with the transport, suggesting that employers paternalistically prevent workers from using their own beliefs and preferences to evaluate the transport. In addition, consistent with the third theoretical prediction, employers hire women significantly more in response to the subsidy to themselves than either of the worker subsidies.

We test whether employers who score highly in a survey module on other-regarding preferences towards women react more to the transport treatment to test the fourth theoretical prediction: The demand response to changing job costs increases in employers' other-regarding preferences (altruistic or paternalistic). We find that more other-regarding employers react almost four times as much to the transport than less other-regarding employers, suggesting that our findings indeed reflect other-regarding discrimination rather than, for example, experimenter demand effects, i.e, employers trying to satisfy the experimenters' preferences.

To evaluate the market's equilibrium behavior, we complement the demand-side experiment with a supply-side experiment: Randomly withholding information on the transport from potential applicants reduces the supply of female and male labor by 15% and 5%, respectively. In particular, the reservation wages of the 770 *applicants*, recruited from the same population but distinct from those of the hiring experiment, increase by BDT 200 (USD 2), that is, by much less than the employers' valuation of female worker transport of around BDT 1,400 (USD 14).

We estimate the model parameters and combine the results of the demand and supply side experiments to study the fifth theoretical prediction: Equilibrium wages decrease in perceived job costs if the demand decreases more than the supply in perceived job costs. We construct the labor demand function by estimating preference parameters in a binary choice model using the hiring choices in the hiring experiment. We construct the labor supply function by aggregating the reservation wages in the application experiment. We combine the two functions to construct equilibria for both genders with and without transport. We find that without transport, equilibrium labor quantities decrease by 16% for women and 7% for men, while wages decrease by 22% for women and 13% for men. We present results from two sets of counterfactuals. First, eliminating paternalistic discrimination reduces the gender employment gap by 22% and increases female wages by 26%. Second, with paternalistic employers, transport interventions may increase total welfare (to employers and workers) more than subsidy interventions.

The extent of paternalism in our experimental setting suggests opportunities for increasing female employment and wages in settings with strong gender norms. While previous research has shown that addressing work-related danger and unsafe transportation can increase the supply of female labor (Park et al., 2021; Field and Vyborny, 2022; Abu-Qarn and Lichtman-Sadot, 2022; Becerra and Guerra, 2023), our findings suggest that these policies can also increase the demand for female labor. This implies compounding benefits from policies that reduce women's perceived job costs (e.g., crime reduction programs and workplace safety regulation) or increase their perceived benefits (e.g., wage laws and subsidies). In addition, these policies may also eliminate socially acceptable excuses for taste-based discrimination, increasing female employment even if employers are selfish.

Our framework could be applied to the study of paternalism in various settings. In the labor market, paternalism may lead employers to fire single workers over workers with families, not promote recent mothers to reduce workloads, or reject applicants from ethnic or political minorities who may face discomfort at work. Outside the labor market, parenting and education decisions, such as how much control to exert (Endendijk et al., 2016) and how to educate children about sex (Kuhle et al., 2015), as well as professional financial advice (Bajtelsmit and Bernasek, 1996) may differ by the gender of the child or advisee.

We contribute to three separate strands of literature. First, we contribute to the literature on discrimination by defining a novel form of discrimination. A large body of literature measures taste-based and statistical discrimination on a variety of characteristics (see, among others, Bertrand and Mullainathan, 2004; Gneezy et al., 2012; Baert, 2018; Bohren et al., 2019; Kessler et al., 2019; Chan, 2022; Macchi, 2022). Paternalistic discrimination differs from taste-based discrimination, as it varies with workers' perceived welfare.[2] It also differs from statistical discrimination in two key ways. First, it is driven by other-regarding rather than self-regarding motives—indeed, employers are willing to forego profits to indulge their paternalism. Second, unlike statistical discrimination, it does not require any uncertainty, as paternalistic employers may overrule applicants' preferences even if job costs are known with certainty. We consider paternalistic discrimination to be most closely related to the psychology literature on benevolent sexism (Glick and Fiske, 1997)—idealized, seemingly positive but stereotypical views of women (e.g., that women should be cherished and protected, Glick et al., 2000; Fraser, 2015; Shnabel et al., 2016; Glick and Raberg, 2018; Offit, 2021). This paper draws on the benevolent sexism literature to formalize the first economic model of paternalistic discrimination.[3]

Second, we contribute to the literature on paternalism and other-regarding preferences by highlighting the role of other-regarding preferences in hiring. Paternalism—limiting the options available to others for their own benefit—drives support for many policies, including banning "repugnant" transactions (e.g., Leider and Roth, 2010; Roth, 2018; Elías et al., 2023), regulating addictive products (e.g., Allcott et al., 2019a,b; DeCicca et al., 2022; Allcott et al., 2022), and protecting boundedly rational or time-inconsistent consumers (e.g., Allcott and Taubinsky, 2015; Allcott et al., 2021). Researchers have also explored the drivers of and responses to paternalism (Uhl, 2011; Ambuehl et al., 2021; Bartling et al., 2023). Most relevant to our setting, other-regarding preferences also drive behavior in the workplace, including wage setting (Akerlof, 1982), effort (Bandiera et al., 2005), resource allocation (Hjort, 2014), and layoff decisions (Guenzel et al., 2023). To our knowledge, our paper is the first to consider how other-regarding preferences differentially affect men and women in the workplace.

Third, we contribute to the growing literature on barriers to female labor force participation, particularly in low-income countries. Among other factors, this literature considers social norms (e.g., Fernández, 2013; Bertrand et al., 2015; Bernhardt et al., 2019; Bursztyn et al., 2020; Field et al., 2021; McKelway, 2023; see Jayachandran, 2021 for an overview) and safety (Chaudhary et al., 2021; Field and Vyborny, 2022; Siddique, 2022) as barriers to female labor supply. Part of this literature specifically examines how physical mobility restricts women's labor supply (e.g., Kondylis et al., 2020; Aguilar et al., 2021; Christensen and Osman, 2023; Cheema et al., 2022). Efforts to study discrimination in South Asia have focused primarily on India, examining differential treatment based on caste (Banerjee et al., 2009; Ito, Takahiro, 2009; Siddique, 2011), religion (Thorat and Attewell, 2007), and gender (Choudhury, 2015; Chowdhury et al., 2018; Islam et al., 2021). This paper is the first to study how paternalism

[2]Our experimental evidence cannot be explained by a distaste parameter that is constant across jobs, so we reject the simplest formulation of the traditional model. As a result, we describe paternalistic discrimination as a novel form of discrimination. The alternative interpretation—as a component of taste-based discrimination that varies with job characteristics—is equally valid.

[3]U.S. law treats benevolent discrimination as any other kind of discrimination (U.S. EEOC, 2007). A separate but related concept in the law literature is *benign discrimination*, which generally refers to discriminatory policies designed to benefit minority or marginalized groups (see, for example, Patty 1989 and Evans 1974).

restricts women's employment, particularly in South Asia.

The rest of the paper proceeds as follows. Section 2 describes the labor model with other-regarding employers and section 3 describes the empirical setting. Sections 4 and 5 present the demand-side experiment with employers and the supply-side experiment with applicants. Section 6 combines the results from the two experiments in the equilibrium model and evaluates a series of counterfactuals. Section 7 concludes.

2 A Labor Market Model with Other-Regarding Employers

In this section, we augment a standard labor market model with other-regarding employers, i.e., employers internalizing their workers' perceived on-the-job welfare, and outline the resulting comparative static predictions. First, we describe two markets with other-regarding employers, one for male workers and one for female workers, and define paternalistic discrimination. Second, we evaluate how increases in workers' perceived job costs affect labor supply and demand and how the demand effects vary with employers' other-regarding preferences. Finally, we investigate how increases in workers' perceived job costs affect equilibrium wages.

2.1 Setup

Market Structure We study two markets, one for each gender $g \in \{m, f\}$.[4] A unit mass of price-taking employers, indexed by k, demand labor in the two markets. A unit mass of male ($g = m$) and a unit mass of female ($g = f$) price-taking workers, indexed by i, supply labor. We use the superscripts A and E to denote preferences and beliefs of workers (i.e., applicants) and employers, respectively. The mass of gender g workers supplying labor is given by L_g^S, and the mass of gender g workers demanded by employers is given by L_g^D. Wages for gender g labor and the quantity of hired gender g labor are determined in equilibrium. w_m^* and w_f^* are the equilibrium wages that equate the labor supply and labor demand for both genders simultaneously. L_m^* and L_f^* are the equilibrium quantities of both genders at these wages.

Workers' Problem Workers supply their labor if their expected utility from working is weakly positive.[5] Worker i's expected money-metric utility from working for employer k depends on the wage w_g, the expected costs c_{igk}, and the disutility associated with the cost of working $u_g^A(\cdot)$, where u_g^A is continuously differentiable and monotonically increasing in c_{igk}, with $u_g^A(0) = 0$.[6] The cost of worker i of gender g working for employer k is given by $c_{igk} = c_g + c_i + c_{kg}$, the sum of (i) a gender-specific cost c_g, known to the worker and the employer, (ii) the worker-specific

[4]The setup generalizes to more groups, each having a separate market.

[5]We study extensive margin decisions to highlight worker selection into different jobs. However, the setup generalizes to intensive margin decisions, for example, by considering every worker supplied as a time unit.

[6]Utility is linear in wages but not costs to match our experimental setting, in which agents are more likely to be risk-neutral for the relatively low wages (one day of salary) than the costs (e.g., sexual assault, Rabin 2013).

cost c_i, known only to the worker, and (iii) the employer-gender-specific cost c_{kg}, known only to the employer. Workers rely on their cost assessments and do not attempt to learn about the employer-gender-specific costs from employers' hiring decisions.[7] We normalize the opportunity costs to be zero and assume that applications are costless such that applicant i of gender g supplies labor if and only if:

$$\mathcal{W}_i^A = \mathbb{E}_i[w_g - u_g^A(c_{igk})] \geq 0. \tag{1}$$

Employers' Problem Employers decide how much male and female labor to demand to maximize their expected utility. Employer k's expected utility is linear and separable in (i) d_{kg}, the non-pecuniary benefits of hiring gender g labor, (ii) $Y^E(L_{kf}, L_{km}) - L_{kf}w_f - L_{km}w_m$, the expected profits of hiring L_{kf} female and L_{km} male workers at wages w_f and w_m, and (iii) fraction $\alpha_{kg} \in (0, 1)$ of the expected on-the-job welfare of the worker, as perceived by employer k, $\mathcal{W}_{kg}$ (henceforth "welfare").[8] The expected production function Y^E is non-negative, concave (see appendix section A.1) and, akin to our empirical setting, not a function of costs, wages, or the selected pool of applicants.[9] Employers understand selection, realizing that the pool of applicants consists only of workers who believe the job will yield positive utility, i.e., for whom $\mathcal{W}_{kg}^A \geq 0$.

We differentiate between two possible types of other-regarding employers:

Definition 1. Altruistic employers internalize their perception of workers' perception of welfare, $\mathcal{W}_{kg}^{E:A} = \mathbb{E}_k[\mathbb{E}_i[w_g - u_g^{E:A}(c_{igk})] | \mathbb{E}_i[u_g^{E:A}(c_{igk})] \leq w_g]$. Paternalistic employers internalize their own perception of workers' welfare, $\mathcal{W}_{kg}^{E} = \mathbb{E}_k[w_g - u_g^{E}(c_{ikg}) | \mathbb{E}_i[u_g^{E:A}(c_{igk})] \leq w_g]$.

We denote the employer's second-order belief about u_g^A by $u_g^{E:A}$ and the employer's risk preferences for gender g workers by u_g^E. Both $u_g^{E:A}$ and u_g^E follow the same functional form assumptions as u_g^A.

Other-regarding employer k thus maximizes the following objective function v_{kg}^E:

$$\max_{L_{kf}, L_{km}} \underbrace{\sum_{g \in \{f,m\}} L_{kg} d_{kg}}_{\text{Taste utility}} + \underbrace{Y^E(L_{kf}, L_{km}) - \sum_{g \in \{f,m\}} L_{kg} w_g}_{\text{Profit}} + \underbrace{\sum_{g \in \{f,m\}} L_{kg} \alpha_{kg} \mathcal{W}_{kg}}_{\text{Other-regarding utility}}, \tag{2}$$

with $\mathcal{W}_{kg} \in \{\mathcal{W}_{kg}^{E:A}, \mathcal{W}_{kg}^{E}\}$.[10]

[7] We assume away that sophisticated workers apply for costly jobs, anticipating that paternalistic employers will protect them from mistakes. This assumption is consistent with empirical evidence: Anticipating discrimination to make inferences about job costs requires extensive contingent reasoning, which a large literature suggests is rare (see Niederle and Vespa (2023) for an overview). Since workers do not anticipate paternalistic discrimination, employers do not worry about workers' preferences for being "paternalized."

[8] Our model is also flexible enough to allow the other-regarding utility to vary with ability, for example, by considering high- and low-skilled workers as separate groups with different welfare weights α_{kg}.

[9] We relax this assumption in the structural model.

[10] Assuming the outside option has zero value, equation 2 is the same if the employer internalizes the welfare of only hired or hired and nonhired workers.

2.2 Defining Discriminatory Preferences

We define discriminatory preferences leading to differential treatment of men and women at a given set of wages (w_f, w_m) and hiring levels (L_{kf}, L_{km}) as follows:

1. *Taste-based discrimination*: $d_{km} > d_{kf}$. The employer receives more (less negative) non-pecuniary returns from hiring male over female workers.

2. *Statistical discrimination*: $\frac{\partial Y^E}{\partial L_{km}} > \frac{\partial Y^E}{\partial L_{kf}}$. The employer expects to receive higher revenues from the marginal male than the marginal female worker.

3. *Other-regarding discrimination*: $\alpha_{km}\mathcal{W}_{km} > \alpha_{kf}\mathcal{W}_{kf}$. The employer expects to receive higher other-regarding utility from the marginal male than the marginal female worker. This is altruistic if employers use their perception of workers' perception of worker welfare and paternalistic if employers use their perception of worker welfare.

Other-regarding discrimination arises because an employer places a higher welfare weight on men's welfare than women's or expects men's welfare to be higher than women's. Three different mechanisms could explain why employers expect men's welfare to be higher even with the same wages: employers (i) believe men have lower costs than women ($\mathbb{E}_k[c_{imk}] < \mathbb{E}_k[c_{ifk}]$), (ii) have different risk preferences for men and women $\left(u^E_{km} \neq u^E_{kf}\right)$, (iii) engage in selection neglect, i.e., they do not condition on $\left(\mathcal{W}^{E:A}_{kg}\right)$ and thus overestimate workers' job costs.

We consider other-regarding distinct from taste-based discrimination because, unlike taste-based discrimination, it varies predictably with perceptions of job costs c_{igk}. We consider other-regarding distinct from statistical discrimination because, unlike statistical discrimination, it can arise even without uncertainty, i.e., when $\mathcal{W}_g = \mathcal{W}^{E:A}_{kg} = \mathcal{W}^E_{kg}$.[11]

2.3 Comparative Statics in Gender-Specific Costs and Wages

In this section, we investigate how labor supply and labor demand by other-regarding employers react to changes in gender-specific costs and wages and how equilibrium wages react to changes in gender-specific costs.

2.3.1 Labor Supply

Workers' perceived welfare is increasing in wages and decreasing in costs. Therefore, workers are less willing to supply their labor if they pay higher gender-specific costs, and more willing to supply their labor if they earn higher gender-specific wages.

[11] Note that other-regarding discrimination can only lead to restricting the employment opportunities of workers willing to work as employers cannot force workers to apply who do not want to apply. In addition, other-regarding discrimination can persist even in repeated markets. Other-regarding employers may never correct biased beliefs (e.g., if they never observe women working the night shift). Moreover, even with perfect information, employers may maintain different preferences over the risks workers face than the workers themselves.

2.3.2 Labor Demand

Next, we describe how the labor demand of other-regarding employers reacts to changes in gender-specific costs and wages.

Other-Regarding Employers and Costs First, we assess how the demand response to changes in gender-specific costs differs between other-regarding and non-other-regarding employers. An increase in c_g has two effects on employers' other-regarding utility: (i) a *direct effect*: the job cost increases, thereby reducing employers' perception of worker utility, and (ii) a *selection effect*: workers with smaller worker-specific cost self-select into the job, thereby increasing employers' perception of worker utility (see appendix A.2). An increase in gender-specific costs unambiguously reduces perceived welfare when holding selection fixed. In this case, if labor demand decreases in response to lower perceived welfare, then employers must place a positive weight on the worker welfare, i.e., they are other-regarding.

Prediction 1 (Other-Regarding Employers)**.** *Holding selection and productivity constant, the labor demand of other-regarding employers is decreasing in gender-specific costs.*

Altruistic and Paternalistic Employers and Costs Second, we assess how the demand response to changes in gender-specific costs differs between altruistic and paternalistic employers. If employers are altruistic, i.e., they internalize their perception of the workers' perception of worker welfare ($\mathcal{W}_{kg}^{E:A}$), then their other-regarding utility is weakly lower when workers receive an amenity rather than a subsidy that allows them to afford the amenity (appendix A.3). Workers are weakly better off receiving the subsidy, as they can use their own valuation of the amenity to decide whether to purchase it. Therefore, if employers demand gender g labor less with the subsidy, they must be paternalistic, i.e., they must use their own beliefs or preferences to evaluate their other-regarding utility. In other words, employers perceive that workers might make a "mistake", i.e., not purchase the amenity even though the employer perceives worker welfare to be higher with the amenity than with the subsidy.

Prediction 2 (Altruistic and Paternalistic Employers)**.** *Holding selection and productivity constant, the labor demand of altruistic employers is increasing weakly more in subsidies to workers than in equally (or lower) priced worker amenities. If labor demand increases less in subsidies than in equally priced amenities, then employers are paternalistic.*

Other-Regarding Employers and Wages We assess how the demand response to changes in gender-specific wages differs between other-regarding and non-other regarding employers. An increase in w_g reduces employers' profit and has two effects on employers' other-regarding utility: (i) *a direct effect*: the wage increases, increasing the employer's perception of worker utility, (ii) a *selection effect*: workers with higher worker-specific cost self-select into the job, decreasing the employer's perception of worker utility (appendix A.4). Thus, holding selection and productivity fixed, the demand for gender g labor decreases in gender-specific wages.

Prediction 3 (Wages)**.** *Holding selection and productivity constant, the labor demand of other-regarding employers is decreasing in gender-specific wages.*

Heterogeneity in α_{kg} The demand response to gender-specific costs and wages changes in α_{kg}. Employers who place a high weight on workers' welfare experience high other-regarding utility loss from higher gender-specific costs. By contrast, their profit loss from higher wages is offset by a larger other-regarding utility gain. Therefore, relatively more other-regarding employers are relatively less willing to hire gender g labor if gender-specific costs are high but relatively more willing to hire gender g labor if gender-specific wages are high (appendix A.5).

Prediction 4 (Heterogeneity)**.** *Holding selection and productivity constant, larger other-regarding preferences α_{kg} lead to a larger demand response to changes in gender-specific costs and a smaller demand response to changes in gender-specific wages.*

2.3.3 Equilibrium Wages

In this subsection, we show that the effect of increases in gender-specific costs on equilibrium wages depends on the size of the cost elasticity of demand relative to that of supply. An increase in gender-specific costs decreases the equilibrium labor quantity as both labor supply and demand contract, but might increase or decrease equilibrium wages depending on the ratio of the demand and supply elasticities with respect to costs (see derivations in appendix A.6). If the ratio is sufficiently large, equilibrium wages decrease because the downward pressure on wages from the decrease in labor demand dominates the upward pressure on wages from the decrease in labor supply.

Prediction 5 (Equilibrium Wages)**.** *Equilibrium wages are decreasing in gender-specific costs if and only if $|\epsilon^D_{c_f}| > m \times |\epsilon^S_{c_f}|$, where $\epsilon^D_{c_f}$ and $\epsilon^S_{c_f}$ are the demand and supply elasticities with respect to female-specific costs and $m \in (0, 1]$ is a function of the substitutability of male and female labor and the demand and supply elasticities with respect to male wages.*

The equilibrium labor quantity and wages of the other gender do not respond to increases in gender-specific costs if male and female workers are separable in the production function, increase if they are substitutes, and decrease if they are complements (appendix A.7). We also derive closed-form solutions for a constant elasticity of substitution production function and a Cobb–Douglas production function in appendix A.8.

3 Setting

We empirically test theoretical predictions 1–5 in two experiments in Dhaka, Bangladesh, in which we sequentially measure the labor demand and supply responses to exogenously varying the perceived job costs to workers. Around 40% of Bangladesh's population lives in urban areas, and about one sixth lives in Dhaka. Dhaka also accounts for one fifth of Bangladesh's GDP and nearly one half of its formal employment (World Bank DataBank, 2023).

Women in Bangladesh struggle to access the labor market, particularly male-dominated occupations (BDHS, 2016; BBS, 2021). About 40% of working-age women in Bangladesh are employed, compared to about 80% of men (World Bank DataBank, 2023). Women also earn less than men, especially in urban areas, where men earn almost 30% more than women (USD 171 versus USD 133 per month, BBS (2018)).[12] This is partly due to the substantial gender segregation in occupations, with men working predominantly in services and women working predominantly in agriculture and industrial production, particularly in the garment sector, where they comprise 80% of the workforce (Farole et al., 2017; Quayyum, 2019).

Restrictive gender norms and labor laws contribute to Bangladesh's large gender employment and wage gaps. In the 2018 Bangladesh World Value Survey, 76% of respondents agreed that "Men should have more right to a job than women," and 67% that "Men make better business executives than women" with similar agreement among men and women, and in urban and rural areas (World Values Survey, 2018). Bangladesh law does not prohibit discrimination on the basis of gender nor mandate equal pay for women and men (World Bank DataBank, 2023). Women in Bangladesh are also legally restricted from operating or cleaning certain types of machinery, carrying heavy items, or working underwater or underground (Bangladesh Labour Act, 2006). While the Bangladesh Labor Act of 2006 lifted a prohibition on women working at night, employers are still required to obtain the consent of women for shifts between 8 p.m. and 6 a.m.; this written consent is not required of men.

Safe transport represents a special concern for women in Dhaka. Women report high rates of physical harassment, such as groping, driver misconduct, and discomfort from overcrowding and crush loading (Rahman, 2010; Aachol Foundation, 2022; Humayun and Islam, 2023). These problems have led providers to establish women-only bus service routes in recent years, though these services offer limited routes and hours (Naher, 2022).

4 The Hiring Experiment: Job Costs and Labor Demand

To measure the labor demand response to variations in gender-specific costs and wages according to predictions 1 to 4 of the model, we conduct a "hiring experiment" with 495 *employers*, individuals with hiring experience in the previous three years, in Dhaka, Bangladesh. Enumerators recruit employers equally from three industries, selected based on recruitment feasibility, different perceived costs to female workers, and high levels of urban employment:

[12] A recent report by the International Labor Organization finds that the factor-weighted mean hourly wage for women is higher than that of men in Bangladesh—a sole outlier among countries studied in the report (International Labour Organization, 2018). However, this finding does not appear to be robust to alternative model specifications (Rahman and Al-Hasan, 2022).

manufacturing, retail/wholesale and services, and education (additional information on these industries is provided in appendix B.2).[13] Enumerators recruit employers in person between April and August 2023 by asking businesses whether any individual with hiring responsibility is interested in participating in the experiment on the spot or later. The employers in our experiment are mostly men (94%), and are, on average, 32 years old (see table 1 for overall summary statistics and appendix table C.1 for summary statistics by industry).[14] 59% are married, and 45% have at least one child. Furthermore, 42% have at least a Bachelor's degree. On average, their businesses have nine male and six female employees, and they have made 27 hiring decisions in the previous three years.

Table 1: Employer Characteristics (N=495)

	Mean	S.D.
Female (%)	6.4	24.6
Age	31.5	7.8
Married (%)	58.6	49.3
Children (%)	45.3	49.8
Bachelor's (%)	42.3	49.5
Male Employees	8.9	24.1
Female Employees	6.0	41.2
Hiring Decisions Last 3 Years	27.0	233.9

Notes: The table shows the means and standard deviations of characteristics of the employers recruited for the hiring experiment.

Employers in the experiment make hiring decisions for a job created by the research team: a one-shift, three-hour Excel workshop followed by a stock market analysis task between 7 p.m. and midnight, with a free and safe transportation service bringing workers home in private six-seater cars after the shift (accompanied by one supervisor per car; see appendix C.2 for a photograph of the shift).[15][16] The applicant pool consists of 580 male and 400 female applicants aged 18 to 60, recruited in booths on 11 university campuses between February and April

[13]We excluded agriculture, a primary employment sector, due to low recruitment feasibility in Dhaka. We asked 80 employers the following question for eight randomly selected applicants about a hypothetical job in their industry: "How dangerous or unpleasant or socially unacceptable do you think this job is for [applicant name], including their commute from and to their home, with 0 indicating a very safe job, equivalent to working from home, and 10 indicating that the job is very dangerous or very unpleasant or very socially unacceptable." The average response for female applicants was 2.5 in manufacturing, 1.0 in retail and services, and 0.3 in education.

[14]The vast majority (89%) of managers in Bangladesh are male, according to official statistics (BBS, 2018).

[15]The cars were mixed-gender. However, this information was not communicated to employers.

[16]Training opportunities at night are common in Bangladesh. In addition, night-shift work is becoming increasingly common as many outsourcing firms work European or US hours (Mamun et al., 2019).

2023 (see appendix C.1 for a photograph of the recruitment).[17] Applicants take two 12-minute back-to-back Excel screening tests incentivized with BDT 2 per correct answer for a total of up to BDT 40 (USD 0.4).[18] On average, male applicants in our experiment are 25 years old and female applicants are 24 years old (table 2). Around one fifth of applicants are married (19% of male and 23% of female applicants), and 12% have children. Female applicants are slightly less experienced than male applicants (89% have up to three years of experience versus 80% of male applicants) but have similar education (36% have a Bachelor's degree versus 39% of male applicants) and Excel screening scores (the average score is 25% versus 23% among male applicants). As we describe in the following sub-section, we measure within-applicants treatment effects and thus do not require balance in observables across gender.

Table 2: Applicant Characteristics in the Hiring Experiment by Gender

	Male (N=580)		Female (N=400)	
	Mean	S.D.	Mean	S.D.
Age	24.8	6.3	23.6	6.0
Married (%)	19.3	39.5	22.8	42.0
Children (%)	12.1	32.6	11.8	32.2
Bachelor's (%)	39.1	48.8	35.7	48.0
$\leq$ 3 Years Work Experience (%)	80.0	40.0	89.0	31.3
Excel Screening Score (%)	22.6	12.5	24.5	13.7

Notes: The table shows the means and standard deviations of characteristics of applicants recruited for the hiring experiment. *Children* is an indicator that is 1 if the applicant has children.

4.1 Hiring Experiment Design

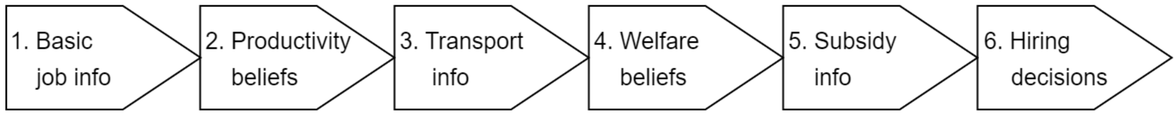
Employers make real hiring decisions and are randomized into different treatment conditions that experimentally vary the perceived job costs for workers, the payoffs received by workers, and the payoffs received by employers. This allows us to test whether employers hire women less when the job costs are perceived to be high (prediction 1)—even when workers can afford safe transport themselves (prediction 2). The variation in payoffs to workers and

[17] We initially targeted 585 men and 405 women to construct 45 hiring pools of nine female and 13 male applicants each (we oversampled men to make hiring choices more realistic); however, five hiring pairs were excluded from the sample as the female applicant was miscoded as male. Results are unchanged when including these five pairs. We conducted recruitment on university campuses anticipating a high concentration of job seekers.and that paternalistic discrimination may be particularly consequential for job seekers early in their careers. We do not restrict participation to university students.

[18] The tests were designed based on a scoping survey with 20 office employers about desired Excel skills.

employers allows us to test whether employers react more to profit than other-regarding concerns (prediction 3). The experiment was carefully designed to avoid potential ethical concerns associated with placing workers in potentially dangerous situations; see appendix B.1. The experiment takes an average of 64 minutes and is conducted in six stages (figure 1).

Figure 1: Stages of the Hiring Experiment



Notes: The figure shows the six stages in the hiring experiment, described in detail below. 1) We provide employers with detailed information about the job. 2) We elicit employers' beliefs about the on-the-job productivity of a subset of applicants. 3) We provide employers with the transport information. 4) We elicit employers' beliefs about the on-the-job welfare of a subset of applicants. 5) We provide employers with the subsidy (employer and worker payoff) information. 6) We elicit employers' hiring decisions.

1. **Basic job information**: In the first stage, we provide employers with basic information about the job. Employers receive the following information about the hiring process: (i) Applicants have applied to a one-day Excel workshop and job from 7 p.m.–midnight and completed an Excel screening test. (ii) Recruited workers will be compensated with BDT 1,500 (USD 15) and receive an Excel workshop completion certificate. (iii) We hire one worker based on each employer's decisions. (iv) Employers receive a base compensation of BDT 500 (USD 5) for their time as well as BDT 5 (USD 0.05) per task completed on the job (out of 100 possible tasks) by their recruited worker.

2. **Productivity beliefs elicitation**: In the second stage, we elicit employers' incentivized beliefs about the on-the-job productivity of four randomly selected applicants (two male-female pairs). Employers predict the number of tasks these applicants will complete if hired based on their first names, gender, marital status, education, years of experience, and Excel screening test scores (see appendix figure C.3 for the experimental interface).[19] Employers are informed that two of these applicants are randomly selected for hire and that they will receive a bonus payment for correctly predicting the productivity of these applicants. Employers guess (i) the probability that each applicant shows up to the shift (incentivized using the binarized scoring rule, see Hossain and Okui (2013)), and (ii) the number of completed tasks conditional on showing up (incentivized with BDT 10, USD 0.1, for guesses within 5 ppts from the truth). To reduce the risk of strategic misreporting, we elicit employers' productivity beliefs before randomizing them to treatment. We also verify that the predictions of the main sample of 495 *Hiring* employers do not differ from

[19]Because of a translation mistake into Bangla, employers were shown "3 years of work experience" instead of "$\geq$ 3 years of work experience" when an applicant had $>$3 years of work experience.

those of 80 separately recruited *Prediction-Only* employers who make no hiring choices and therefore have no incentive to adjust their predictions to their hiring choices.

3. **Transport information randomization**: In the third stage, we randomize employers into one of two transport treatments that experimentally vary their perception of workers' job costs while holding constant the perceived worker selection and productivity:

   (a) *Transport* (50%): Employers are informed about the transport with supervisors.

   (b) *No Transport* (50%): Employers are not informed about any transport.

   The randomization allows us to test theoretical prediction 1: Demand for female labor is lower without safe transport. To hold constant the perceived selection of applicants willing to work across treatments, we inform employers that all applicants have applied for the job without knowing about the transport. To hold constant the perceived productivity of applicants across treatments, we inform employers in the *Transport* treatment that workers will only learn about the transport after completing the shift, i.e., that the transport cannot affect their show-up probability or on-the-job performance. To hold constant beliefs about applicants' beliefs across treatments, i.e., to ensure that also employers in the *No Transport* treatment (where we do not mention transport) know that applicants do not expect transport, we inform employers in both treatments "Aside from the job description before, no other benefits (such as flexible hours, work-from-home, [transport], or future employment) are offered to any applicant." ("transport" is only included in the *No Transport* treatment). We verify comprehension of the experimental set-up in five comprehension questions administered after the treatment assignments (see appendix section B.6.1). We also find that employers perceive workers to be very likely to take the offered transport (i.e., high compliance) and no evidence for information spillovers (i.e., no contamination).[20]

4. **Cost beliefs elicitation:** In the fourth stage, we elicit employers' beliefs about the job costs (including the commute) in terms of danger, unpleasantness, and social acceptability on a scale from 0 to 10. We elicit employers' beliefs for the same four applicants for which they make productivity predictions (see appendix figure C.4 for the experimental interface). We do not inform employers of applicants' reported costs to reduce anchoring, nor do we attach any experimental incentives to the elicitation to reduce strategic report-

[20]Only one *Transport* employer believes that applicants will not take the transport. To prevent information spillovers (i.e., employers in the *No Transport* condition learning about the transport from previous workers), we started the shifts only after roughly half (57%) of the hiring experiment was completed (results are robust to restricting the sample to all employers surveyed before this shift). Only six employers in the *No Transport* treatment believe that applicants will get home by provided transport (three of these are excluded from the analysis due to incorrectly answering understanding questions used for screening comprehension). The vast majority of *No Transport* employers (98%) believe applicants will use public transport or a ride share (Uber, CNG, Rikshaw).

ing.[21] We find no significant differences between *Hiring* and *Prediction-Only* employers, suggesting results are not driven by strategic misreporting to justify hiring decisions.

5. **Subsidy randomization**: In the fifth stage, we cross-randomize employers into one of five subsidy treatments that experimentally vary the payments received by workers and employers while holding constant worker selection and productivity:

   (a) *No Subsidy* (40%): Male and female workers receive BDT 1,500 (USD 15) for completing the shift. Employers receive BDT 500 (USD 5) for hiring any worker.

   (b) *Male Worker Subsidy* (20%): Male workers receive BDT 2,500 (USD 25), and female workers BDT 1,500 (USD 15) for completing the shift. Employers receive BDT 500 (USD 5) for hiring any worker.

   (c) *Female Worker Subsidy* (20%): Male workers receive BDT 1,500 (USD 15), and female workers BDT 2,500 (USD 25) for completing the shift. Employers receive BDT 500 (USD 5) for hiring any worker.

   (d) *Employer Subsidy for Hiring Women* (19%): Male and female workers receive BDT 1,500 (USD 15) for completing the shift. Employers receive BDT 500 (USD 5) if their hired worker is a man, and BDT 1,500 (USD 15) if it is a woman.

   (e) *Employer Subsidy for Hiring Men* (1%): Male and female workers receive BDT 1,500 (USD 15) for completing the shift. Employers receive BDT 1,500 (USD 15) if their hired worker is a man, and BDT 500 (USD 5) if it is a woman.

   The randomization allows us to test theoretical predictions 2 and 3: Demand for female labor is higher with safe transport than with subsidies paid to female workers; and labor demand is increasing more in subsidies paid to employers than workers. Qualitative interviews suggest that it is common knowledge that workers can afford an Uber (costing $\leq$ BDT 500 or USD 5) or professional car service (costing $\leq$ BDT 800 or USD 8) using the subsidy of BDT 1,500 (USD 15). We decided against an alternative design in which we inform employers that workers can use the subsidy to purchase transport from us to avoid deception (as we provide transport to all workers; see appendix B.1 for a discussion of ethical considerations).

   We take the following steps to hold constant both perceived worker selection and productivity across subsidy treatments. First, employers draw a piece of paper to determine their treatment assignment. This procedure signals to employers that all subsidy outcomes are due to chance. Second, the *Employer Subsidy for Hiring Men* is included to prevent asymmetrical subsidies that could signal that women are deferentially qualified than men (enumerators describe all treatments but not the relative frequencies (in parentheses) to

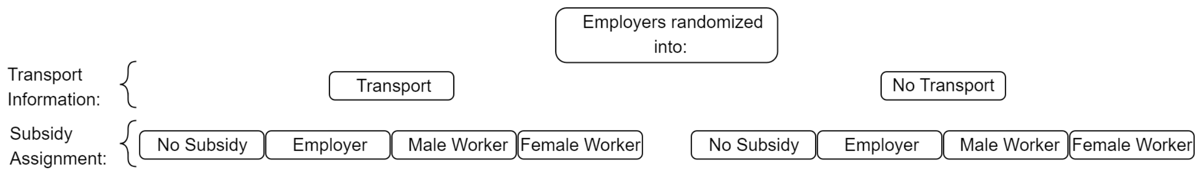
[21]For example, if we promised to convey the response as advice to the applicant, employers with a strong distaste for hiring women might misleadingly report a high cost.

the employers). Third, to hold constant perceived selection and productivity, employers are informed that workers will be surprised by the subsidies at the end of the shift.

6. **Hiring**: In the sixth stage, employers make twelve hiring decisions between two randomly selected applicants. For each applicant, employers are shown the same characteristics as employers in the prediction questions (see appendix figure C.5 for the experimental interface). Each employer makes decisions for two male–male pairs and ten mixed-gender pairs in random order. We did not include two female–female pairs because we wanted to keep the female-to-male ratio similar to that observed in labor markets in Bangladesh. Two mixed-gender pairs were already included in the productivity and cost beliefs elicitation stages. One of these two pairs comes from the application experiment (described in section 5) to incentivize productivity beliefs (see stage 2). The remaining eleven pairs are shown to eleven employers each, implementing a different pair per employer so that we implement one hiring choice per pair (see appendix B.5 for a description of the matching process). Employers are informed that one of their decisions will be implemented and that their identity will not be revealed to any workers.

We make several design choices to reduce experimenter demand effects across treatments as much as possible (treatments are summarized in figure 2). First, all treatments are assigned across employers to make it harder for participants to infer the study purpose. Second, all interviews are conducted privately and anonymously. Third, participants are informed about all subsidy treatments regardless of their assignments, holding constant demand effects for hiring women across subsidy treatments.

Figure 2: Experiment Treatment Arms



Notes: Employers were cross-randomized into two transport and four subsidy treatments, described above.

4.2 Hiring Analysis: Empirical Specification

We next test whether the design and randomization were successful in keeping constant other forms of discrimination across treatment arms and present our estimating equation.

We identify *within-applicant* differences in hiring across treatments, allowing us to rule out a myriad of endogeneity concerns (even though balance is not required, we provide applicant characteristics by treatment in appendix table C.3). The transport treatment was stratified by applicant and by employer industry.[22] We restrict the sample to employers who answer all understanding questions correctly (94%, see appendix B.6.1 for the understanding questions) and

[22] As the subsidy treatments were drawn on-the-spot, they were not stratified.

who are not assigned to the *Employer Subsidy for Hiring Men*, a treatment we only include for perceptions of fairness and symmetry (see section 4.1). Employer characteristics and productivity beliefs are balanced across treatment arms (appendix tables C.2 and C.3) and predictions do not differ between *Hiring* and *Prediction-Only* employers (appendix table C.4). In addition, employers are more likely to report basing their hiring decisions on safety but not taste or statistical concerns without transport (employers in the *Female Subsidy* expected women to generate slightly lower revenues: BDT 29, USD 0.3, p=0.04).

We estimate the following equation among all female applicants shown to at least two employers:[23]

$$\begin{aligned} H_{kii'} = &\alpha + \beta_1 NT_k + \beta_2 MS_k + \beta_3 FS_k + \beta_4 ES_k + \beta_5 (NT_k \times MS_k) \\ &+ \beta_6 (NT_k \times FS_k) + \beta_7 (NT_k \times ES_k) + \mu_i + \mu_j + \beta_7' X_{i'} + \epsilon_{kii'} \end{aligned} \tag{3}$$

where $H_{kii'}$ is an indicator that is 1 if employer k hires female applicant i over male applicant i'. NT_k, MS_k, FS_k, and ES_k are indicators that are 1 if employer k is assigned to the *No Transport*, the *Male Subsidy*, the *Female Subsidy* or the *Employer Subsidy* treatment, respectively. μ_i and μ_j are strata fixed effects, i.e., female applicant and employer industry fixed effects, and $X_{i'}$ is a vector of all male applicant characteristics shown to the employer (Excel screening score, education, work experience, and marriage status).[24] We estimate Huber–White robust standard errors clustered at the employer level (the level of randomization).

This specification allows us to test whether employers from the same industry hire the same woman differentially across treatment arms, even when conditioning on all characteristics of the alternative applicant shown to the employer. Specifically, we test:

- Prediction 1: Demand for female labor is lower without than with safe transport: $\beta_1 < 0$.
- Prediction 2: Demand for female labor is higher with safe transport than with subsidies paid to female workers: $\beta_1 + \beta_3 + \beta_6 < 0$.
- Prediction 3: Labor demand is increasing more in subsidies paid to employers than workers: $\beta_2 < \beta_4$, $\beta_3 < \beta_4$.

The first prediction implies that employers are other-regarding. Without taste, profit, or reputation concerns, employers do not have *self*-regarding motives to hire fewer women without transport. The second prediction implies that employers are paternalistic. An altruistic employer's utility from hiring women relative to men is strictly greater in the *No Transport+Female Subsidy* treatment than the *Transport+No Subsidy* treatment: Independent of

[23]We exclude seven female applicants from the application experiment (used to incentivize beliefs, see section 4.1, stages 2 and 4) shown to only one employer. By design, all applicants in the hiring experiment were shown to multiple employers.

[24]As each pair is shown to 11 employers, these controls only capture the characteristics of the man among the 12th prediction pair.

women and men's valuation of transport, women are strictly better off (they receive a subsidy larger than the cost of transport) while men are strictly worse off (they do not receive transport). Employers may only hire women less with the subsidy than the transport if they expect to earn less other-regarding utility because they (i) perceive the subsidy's value to be lower than that of the transport, and (ii) believe women may not purchase the transport because they undervalue it. The third prediction implies that labor demand is locally downward sloping in wages.

Finally, we assess heterogeneity in hiring by employer characteristics:

- Prediction 4: Employers with larger concerns for women's welfare respond more to safe transport and subsidies paid to female workers.

We test whether the response to the transport and female worker subsidies is larger among:

1. Employers who reported above-median agreement with paternalistic laws in India that restrict women from working at night (on a 0–10 scale with a median response of 8).
2. Employers who reported above-median agreement with the statement that women should not work at night, even if they want to (on a 0–10 scale with a median response of 6).
3. Employers who transferred above-median to the female worker in a three-way dictator game between themselves and two workers from the application experiment (to ensure that employers did not simply try to compensate workers for not hiring them; BDT 0–100 with a median transfer of BDT 30 or USD 0.3 to male and female workers).[25]
4. Employers who reported below-maximum agreement with the statement that women should be protected from harmful jobs, even against their will (on a 0–10 scale with a median response of 10).

We also test whether the response to the transport and subsidies is larger among employers with an above-median Kling Mean effects index of the four measures (Kling et al. (2007).[26]

These heterogeneity analyses also serve a second purpose: If treatment effects are larger among employers with more other-regarding attitudes towards women, then behavior in the experiment likely reflects true other-regarding preferences rather than, for example, experimenter demand effects. For experimenter demand effects to drive the observed behavior, employers would have to perceive paternalistic discrimination to be the norm; that is, that protecting women is desirable. We also do not differentiate between employers who hire women because they altruistically care about them or to avoid feeling guilty or receive "warm glow" (Andreoni, 1990), consciously or sub-consciously (e.g., through motivated beliefs Bénabou and Tirole (2005)).

[25]Dictator game transfers are not a direct measure of α_{kg}. In our model, employers should keep the entire amount whenever $\alpha_{kg} < 1$. Instead, we consider the dictator game transfers as a proxy of underlying individual-level other-regarding preferences.

[26]We find similar results when using a correlation-adjusted index Anderson (2008)).

4.3 Results: Job Costs and Labor Demand

This subsection presents the results of our experimental tests of predictions 1 to 4. We first test whether information about the transport changed employers' beliefs about job costs, and then test whether exogenously changing perceived job costs or payments received by the workers or employers changes hiring decisions.

Not informing employers about the transport increases their perceived job costs (including commute, section 4.1, stage 4) by 1.6 points ($p<0.01$) from a baseline of 0.9 for male applicants and by 3.1 points ($p<0.01$) from a baseline of 3.2 for female applicants (appendix table C.3).

Consistent with prediction 1, not informing employers about the transport reduces the share of hired female applicants by 22% (-10ppts, $p<0.01$) from a baseline of 45% (figure 3, bars 1 and 2).[27] The reduction in demand for female labor seems to be driven by changes on the extensive rather than the intensive margin: *No Transport* reduces the share of employers that hire at least one woman by 48% ($p=0.01$) but does not significantly reduce the number of women hired among employers that hire at least one woman (appendix table C.6). This result suggests that employers who adhere to a protective norm towards women may completely stop hiring them without transport.

As employers only make hiring choices over applicants willing to take the job, these results imply that employers restrict women's employment opportunities when employers consider the opportunities unsafe. Moreover, we find that this employer behavior varies with applicant characteristics: Employers respond most strongly to the ride information when the female applicant has less experience than the male applicant (appendix figure C.8).

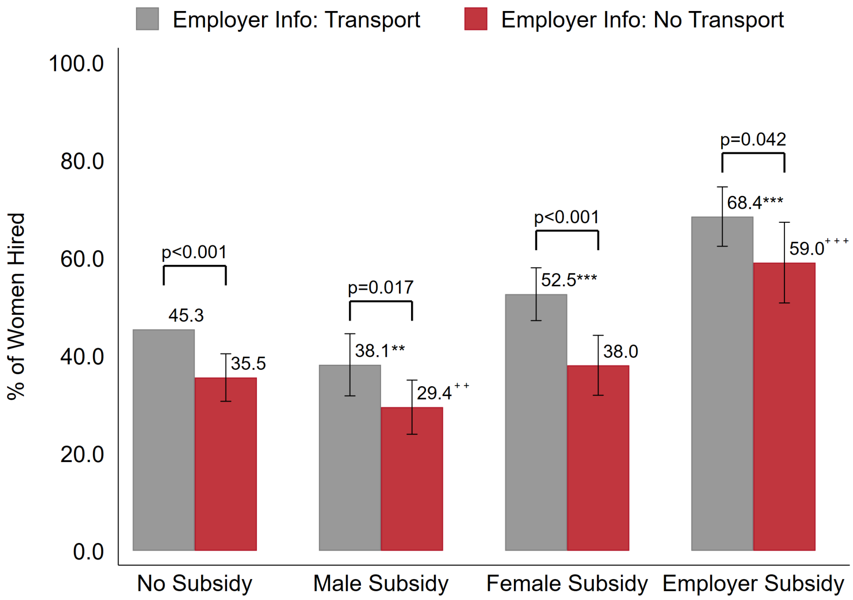
Consistent with prediction 2, employers behave paternalistically rather than altruistically: They hire women more under the *Transport+No Subsidy* than under the *No Transport+Female Subsidy* condition (45% versus 38%, bars 1 and 6, $p=0.02$), i.e., when they know that women receive an additional BDT 1,000 (USD 10). In other words, employers do not hire women without transport—even when women can afford safe transport themselves. This is consistent with 93% of these employers agreeing that women should be protected even against their will (choosing 6–10 on the Likert scale, see section 4.2). By contrast, the male subsidy increases male hiring with and without transport (+13%, $p=0.03$, and +9%, $p=0.04$). In addition, consistent with prediction 3, the employer subsidy increases hiring more than the worker subsidies with and without transport (+51%, $p<0.01$, and +66%, $p<0.01$).

Using the change in hiring in response to applicant characteristics and the subsidy treatments, we estimate employers' valuation of the transport in terms of worker qualifications and payments to female workers or employers themselves. The coefficients on the Excel screening score, the *Female Subsidy*, and the *Employer Subsidy* imply that employers value the safe trans-

[27] The high female hiring rate is consistent with responses to an open-ended question suggesting that employers believed the study's goal was to test their ability to hire the most qualified workers. Accordingly, the enumerators reported that the employers attempted to reduce their biases against women as much as possible.

port as much as a 7ppt (0.5SD) increase in Excel score, BDT 1,371 (USD 13) to the worker, or BDT 427 (USD 4) to the employer (appendix table C.5, columns (1) and (2)).

Figure 3: Hiring by Transport Information and Subsidy Assignment



Notes: The graph shows results from equation 3, i.e., the share of women hired by whether the employer knows about the transport or was offered no subsidy, a male or female worker subsidy, or an employer subsidy for hiring women. Each bar is the sum of the control mean and the relevant regression coefficients. We show 95% confidence intervals based on the estimated standard errors of the linear combinations of the regression coefficients. Asterisks are from p-values from Wald tests comparing hiring rates between *No Subsidy* and each of the subsidies with transport, $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$ (on the gray *Transport* bars, only), and pluses from comparing *No Subsidy* and each of the subsidies without transport, $p < 0.10^{+}$, $p < 0.05^{++}$, $p < 0.01^{+++}$ (on the red *No Transport* bars, only). P-values between bars compare hiring rates with and without transport within subsidies.[28]

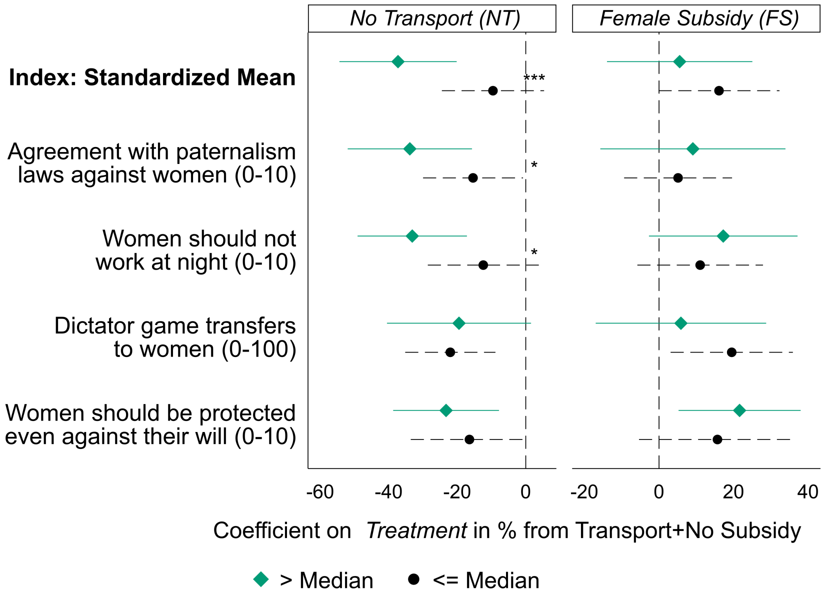
Finally, consistent with prediction 4, employers with stronger other-regarding preferences respond more strongly to the *No Transport* treatment (and directionally more to the *Female Subsidy* for three out of four measures, see figure 4).[29] Overall, we do not find substantial heterogeneity for two measures, for which we also observe little heterogeneity in the underlying responses, making meaningful employer classification difficult: Consistent with the 50–50 norm (Andreoni and Bernheim, 2009), 71% of employers gave the same dictator game transfers to men and women (85% within BDT 10), and 59% fully agreed (10 out of 10) that women should be protected against their will (only 4% disagreed, 0–4 out of 10).[30]

[28]The p-values comparing the effect of the female with the male subsidy, with and without transport, are $p = 0.99$ and $p = 0.49$, respectively (not shown). The p-values comparing the effect of the female with the employer subsidy, with and without transport, are $p < 0.01$ and $p < 0.01$, respectively (not shown).

[29]The index is formed as the mean of the standardized continuous and not binary variables. Thus, the treatment effects do not need to be the averages of the treatment effects of the binary measures.

[30]A body of literature questions the value of the dictator game for measuring altruism, suggesting that giving may be an artefact of the experimental environment with little external validity (Cherry et al., 2002; Bardsley, 2008; Di Tella et al., 2015; Winking and Mizer, 2013).

Figure 4: Hiring by Transport Information, Female Subsidy and Other-Regarding Preferences



Notes: The graph shows the coefficients on the *No Transport* and *Female Subsidy* indicators from regression 3, respectively. Regressions are run separately among different subsets of employers (see section 4.2). That is, each coefficient shows how much employers in that group reduce female hiring when they do not know about the safe transport or increase female hiring when they know about the female subsidy. Asterisks from comparing the coefficients across subsamples. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Results are robust to a series of different regression specifications (appendix table C.5). They are robust to removing applicant fixed effects or all covariates, and selecting covariates using Belloni et al. (2014)'s post-double selection Lasso method. They are also robust to including employers who answer understanding questions incorrectly, to including only employers who report that women in the *Transport* treatment will get home using provided transport and women in the *No Transport* will not, and to including only employers surveyed before the first night shift (for whom spillovers are impossible). They are also robust to excluding the applicants from the application experiment. Finally, results are robust to clustering standard errors at both the employer and applicant level (Cameron et al., 2011) and using a Logit specification. Employers respond more to the transport information in a robustness check in a small sample of 41 employers, in which we reduced the salience of gender by presenting the subsidies as random payments to Candidate 1 or Candidate 2 (see appendix figure C.6 for the experimental interface).[31] This result is consistent with enumerator reports that employers made a conscious effort to reduce their biases against women as much as possible in the main study when the experiment's relationship to gender was more salient. Thus, reducing the salience of gender in the experiment *increases* paternalistic discrimination. By contrast, if the results were driven by experimenter demand effects, reducing the salience of gender in the experiment should *reduce* paternalistic discrimination.

[31] The higher female hiring rate with transport is explained by women's Excel screening score being 1.8 points higher than men's in this subsample.

4.4 Mechanisms

We assess the relative importance of three potential drivers of paternalistic discrimination (see section 2.2): employers' beliefs about job costs, employers' attitudes toward risk, and selection neglect (that is, failure to condition on applicants' selection into the applicant pool).

1. **Costs**: As we discussed in the previous sub-section, employers believe that job costs (on a 0–10 scale, see section 4.1, stage 4) are significantly higher without transport than with transport, and more so for women than men.

   Employers also believe women underestimate job costs more than men, both on the extensive and intensive margin. We elicited first- and second-order beliefs about job costs from 80 *Beliefs-Elicitation* employers, who guessed productivity and costs for eight applicants from the application experiment (second-order beliefs were incentivized with BDT 5, or USD 0.05, per correct answer).[32] Controlling for other characteristics, employers believe that 56% of women and 31% of men underestimate the costs ($p<0.01$) and that the average conditional mistake (the difference between first- and second-order beliefs) is 1.8 for women versus 1.4 for men ($p<0.01$).[33] We also find that employers react more to the transport (though not significantly so) if they believe the female applicant to underestimate the costs (i.e., for whom their first-order cost beliefs, see section 4.1, stage 4, are larger than their incentivized second-order beliefs about the average reported costs of women willing to do the job in the application experiment, see appendix figure C.9).

   However, employers *overestimate* the frequency of negative events on the night shift, and more so for women than men. We incentivized employers to guess the results of a small survey with 20 male and 20 female night-shift workers (BDT 5, or USD 0.05, per correct answer). Employers believe that (i) 3.3 men and 4.1 women were in a car accident ($p<0.01$), with the true numbers being 5 and 2, (ii) 4.3 men and 6.3 women were robbed ($p<0.01$), with the true numbers being 2 and 4, and (iii) 3.2 men and 8.8 women were attacked or assaulted ($p<0.01$), with the true numbers being 1 and 3.

2. **Risk Preferences**: Employers who believe *women should be* rather risk-averse but not employers who believe *women are* rather risk-averse reduce hiring significantly more without transport (see appendix figure C.9). We measure both employers' risk preferences for women and perceptions about women's risk preferences by adapting a question from the Global Preference Survey (Falk et al., 2018, 2023): "In your opinion, on a scale of 0–10, how willing to take risks should women be [are women]?"[34]

[32] These employers are different from the 80 *Prediction-Only* employers who made predictions about applicants from the hiring experiment.

[33] Note that we do not observe true costs on the Likert scale.

[34] We opted not to elicit incentivized risk preferences as gambling is illegal in Bangladesh.

These results suggest that risk preferences may drive paternalistic discrimination, and offer additional evidence that employers are paternalistic rather than altruistic.[35]

3. **Selection Neglect**: We find no evidence that selection neglect drives paternalistic discrimination in the experiment. We test for selection neglect by eliciting employers' perceptions of differences in reported job costs between applicants willing and unwilling to take the job at BDT 1,500 (USD 15) in the application experiment (see section 4.1, stage 4). If selection neglect drives discrimination (e.g., by causing employers to evaluate the selected pool of willing applicants as if they were a random draw from the general population), we would expect employers who underestimate the cost differences to respond more strongly to treatment (see, for example, Exley and Nielsen (2022)). However, we find that employers overestimate the reported cost differences between willing and unwilling applicants (2.3 for women and 1 for men, $p<0.01$, compared to the true values of 0.8 and 0.5) and that hiring behavior does not vary with the perceived difference (see appendix figure C.9).

These results suggest that paternalistic discrimination is due to employers believing that 1) job costs are high and women underestimate them, and 2) women should be more risk-averse.

5 The Application Experiment: Job Costs and Labor Supply

To measure the labor supply response to variations in gender-specific costs, we conduct an "application experiment" with *applicants* for the Excel workshop and job on the night shift. We recruit 391 men and 379 women aged 18 to 60 through in-person recruitment drives on 11 university campuses in March and April 2023 in Dhaka, Bangladesh.

The pool of applicants is similar to that in the hiring experiment (table 3, see table 2 for applicants in the hiring experiment). The male applicants in our experiment are, on average, 26 years old, and the female applicants are, on average, 23 years old. Around one quarter of applicants are married (26% of men and 24% of women), and less than one fifth have children (18% of men and 14% of women). Female applicants are less experienced than male applicants (89% have have up to three years of experience versus 72% of male applicants) but have similar education (9% have a Bachelor's degree versus 14% of male applicants) and Excel screening scores (the average score is 26% versus 25% among male applicants).

[35] We do not believe that low reported risk-preferences for women simply proxy low perceived costs for women or paternalistic attitudes. We observe a very low correlation between risk-preferences and perceived costs (r=-0.02) and low correlations between risk-preferences and agreement with paternalism laws in India (r=-0.12), the statement that women should be protected even against their will (r=-0.08), and the statement that women should not work at night (r=-0.18).

Table 3: Applicant Characteristics in the Application Experiment by Gender

	Male (N=391)		Female (N=379)	
	Mean	S.D.	Mean	S.D.
Age	25.9	7.8	22.9	6.4
Married (%)	26.3	44.1	23.5	42.4
Children (%)	18.4	38.8	13.5	34.2
Bachelor's (%)	14.3	35.1	8.7	28.2
$\leq$ 3 Years Work Experience (%)	72.1	44.9	88.9	31.4
Excel Screening Score (%)	24.8	11.5	26.3	12.1

Notes: The table shows the means and standard deviations of characteristics of applicants in the analysis sample of the application experiment. *Children* is an indicator that is 1 if the applicant has children.

5.1 Application Experiment Design

Applicants make real application decisions and are randomized into different treatment conditions that experimentally vary the perceived job costs for workers. The experiment takes an average of 63 minutes and is conducted in four stages described below.

1. **Applicant screening:** In the first stage, applicants take two 12-minute back-to-back Excel screening tests incentivized with BDT 2 per correct answer for a total compensation of up to BDT 40 (USD 0.4). After completing the tests, applicants are informed that the workshop and job will be from 7 p.m.–midnight, that all hired workers will receive an Excel certificate of completion, and a fraction of workers will be promoted and receive a promotion benefit of BDT 500 and a promotion certificate.

2. **Transport information randomization:** In the second stage, we randomize applicants into one of two transport treatments that experimentally vary the perceived job costs:[36]

   (a) *Transport:* Applicants are informed about the safe transport home.

   (b) *No transport:* Applicants are not informed about the safe transport home.

3. **Cost beliefs elicitation:** In the third stage, we elicit applicants' unincentivized beliefs about job costs (see section 4.1).

[36] In addition, we also experimentally vary the perceived non-wage benefits through two treatments: (i) *High Promotion:* Applicants are informed that 90% of workers hired for the job are promoted. (ii) *Low Promotion:* Applicants are informed that 10% of workers hired for the job are promoted. In the *Low (High) Promotion* arm, promotions are conducted automatically, selecting the 10% (90%) highest-scoring workers. Applicants determine their promotion treatment assignments by drawing a piece of paper, signaling to them that all promotion assignments are due to chance.

4. **Reservation wage elicitation:** In the fourth stage, we elicit applicants' reservation wages using the Becker–DeGroot–Marschak mechanism (Becker et al., 1964) (see figure C.7 for the experimental interface). Applicants then randomly draw a wage between BDT 100 (USD 1) and BDT 5,000 (USD 50) from the following distribution (applicants are informed about the wages in the distribution but not the probability of each wage):[37]

Table 4: Random Wage Distribution in the Application Experiment

BDT	100	250	500	1,000	2,000	3,000	4,000	5,000
%	40%	40%	15%	1%	1%	1%	1%	1%

Applicants are hired if the random wage is at least as high as their reported reservation wage. In total, 231 men and 183 women are hired as part of the application experiment.

5.2 Application Analysis: Empirical Specification

We next test whether the design successfully varied perceived job costs and present the estimating equation that allows us to estimate applicants' valuation of safe transport. We restrict the sample to applicants who answer all understanding questions correctly (91% of male and female applicants, see appendix B.6.2 for the understanding questions). Both male and female applicant characteristics are balanced across treatment arms (appendix table C.7).

We estimate the following equation separately among male and female applicants:

$$\overline{w}_i = \alpha + \beta_1 NT_i + \beta_2' X_i + \epsilon_i \tag{4}$$

where $\overline{w}_i$ is the stated reservation wage of applicant i, and NT_i is an indicator that is 1 if applicant i is assigned to the *No Transport* treatment. X_i is a vector of applicant controls (as randomization was across applicants), including the applicant's age, Excel screening score, education, years of experience, and marital status.[38] ϵ_i are Huber–White robust standard errors.

5.3 Results: Job Costs and Labor Supply

We first test whether information about the transport changed applicants' beliefs about job costs and then whether exogenously changing perceived job costs changes application decisions. Not informing applicants about the transport increases their perceived job costs by 0.4

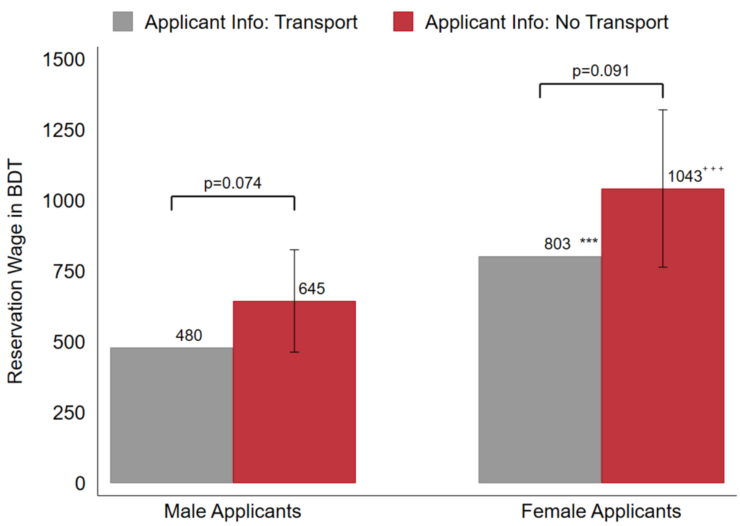
[37] We noticed a correlation between the random lottery wage and applicant characteristics mid-survey. In particular, women, educated applicants, and married applicants without children drew higher random wages on average. As we were concerned that enumerators might be redrawing the wages to draw higher wages for applicants with higher opportunity costs, we discussed our concerns with the survey firm and started closely supervising the surveys. Enumerators never redrew a wage while we were watching, and we do not observe any correlation between the stated reservation wage and the randomly drawn reservation wage.

[38] We also control for indicators for whether the applicant was assigned to the *High Promotion* rate and its interaction with the *No Transport* treatment (see footnote 36).

points (p>0.1) from a baseline of 2.3 among male applicants and by 0.8 points (p=0.03) from a baseline of 5.9 among female applicants (on a scale from 0–10, appendix table C.7).

Not informing applicants about the transport increases the reservation wage of male applicants by 34% (BDT 165, USD 2, p=0.07) from a baseline of BDT 480 (USD 5) and that of female applicants by 30% (BDT 240, USD 2, p=0.09) from a baseline of BDT 803 (USD 8, figure 5). Women's significantly higher reservation wage with transport (p<0.01) is consistent with women's higher perceived costs even with transport. Interestingly, the valuation of the transport by both male and female applicants is similar to the expected transport price in Dhaka, suggesting that the applicants considered safe transport as a means of reducing their transport costs. By contrast, employers value the transport significantly more for female workers, at BDT 1,371 (USD 13, p<0.01, section 4.3). Starting from a baseline wage of BDT 1,500 (USD 15), the wage paid in the experiment, male labor supply decreases by 5% (4ppts, p>0.01) without transport and female labor supply by 15% (13ppts, p=0.06, appendix table C.8).

Figure 5: Application Rates by Applicant Gender and Transport Assignments



Notes: The graph shows results from equation 4 within gender (winsorized at the 95th percentile). Each bar is the sum of the control mean and the relevant regression coefficients. We show 95% confidence intervals based on the estimated standard errors of the regression coefficients. Asterisks are from p-values from Wald tests comparing reservation rates across genders with transport, $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$ (on the gray *Transport* bars, only), and pluses from reservation wages across genders without transport, $p < 0.10^{+}$, $p < 0.05^{++}$, $p < 0.01^{+++}$ (on the red *No Transport* bars, only). P-values between bars compare reservation wages with and without transport within genders.

Results are robust to a series of different regression specifications (appendix table C.8). They are robust to truncating or to not winsorizing reservation wages, including or excluding outliers, removing covariates or selecting them using Belloni et al. (2014)'s post-double selection Lasso method, and including applicants who answer understanding questions incorrectly.

6 Structural Estimation: Job Costs and Market Equilibrium

To test equilibrium prediction 5 of the model and quantify the effect of paternalistic discrimination on equilibrium wages, we combine the results from the labor demand and supply experiments described in the previous two sections in an equilibrium model. The model allows us to identify the equilibrium effects of changing perceived costs for workers while allowing worker selection and productivity to vary with costs. First, we estimate the parameters of the employers' utility function using the employers' decisions in the hiring experiment and construct total labor demand as a function of wage. Second, we construct the labor supply function using reservation wages in the supply-side experiment. Third, we combine the demand and supply functions to construct equilibria for both genders. Finally, we benchmark the importance of paternalistic discrimination against other sources of the gender employment and wage gaps and assess the cost-effectiveness of safe transport and subsidy interventions.

6.1 Labor Demand

We simulate the labor demand function in three steps. First, we estimate employers' preferences, i.e., how employers trade off taste, profit, and other-regarding concerns in hiring decisions. Second, we estimate how employers' productivity and welfare beliefs respond to changes in wages and transport (as beliefs were held constant in the experiment). Third, we use the estimated preferences and predicted beliefs to simulate labor demand. We first describe the parameterization of the demand function and then the three individual steps to simulate it: estimating preferences, predicting beliefs, and simulating the labor demand curve.

6.1.1 Parametrization

We modify equation 2 for paternalistic employers to allow selection and productivity to vary with wages and transport and employers to be from different industries. We simulate separate markets for each industry and gender labor such that each market is a gender-industry combination. Employers and workers do not move between industries. The markets for male and female labor clear simultaneously by industry. We normalize d_{km} to zero and drop the gender subscript such that d_k is the employer's taste for working with women.

Employer k's expected utility from hiring applicant i of gender g in industry j in decision $t \in [0, 10]$ at wage w_{jg} and without transport $NT \in \{0, 1\}$ is given by the following equation:

$$\begin{aligned} u_{kit} &= v_{kit} + \varepsilon_{kit} \\ &= \underbrace{d_k}_{\text{Taste utility}} + \underbrace{\beta_j \Pi_{kit}(w_{jg}, NT_{jg})}_{\text{Profit utility}} + \underbrace{\alpha_{kg} \mathcal{W}^E_{kit}(w_{jg}, NT_{jg})}_{\text{Other-regarding utility}} + \varepsilon_{kit}, \end{aligned} \tag{5}$$

where v_{kit} is the observed utility that varies according to the applicant's gender, and expected profit and other-regarding utility, and $\varepsilon_{kit} \sim EV1$ is an unobserved demand shock. The employer's *preferences* are given by taste parameter $d_k \sim \mathcal{N}(d_j, \sigma^d_j)$, preference for profits β_j, and other-regarding utility weights $\alpha_{kg} \sim \mathcal{N}(\alpha_{jg}, \sigma^\alpha_{jg})$. That is, as every employer makes 10 choices between a male and a female applicant, we allow the each employer's hiring choices to be correlated. The employer's *beliefs* about the worker's profit and welfare are given by $\Pi_{kit}(w_{jg}, NT_{jg})$ and $\mathcal{W}^E_{kit}(w_{jg}, NT_{jg})$.

6.1.2 Estimating Employer Preferences

We estimate employer preferences using a random coefficient binary choice model that exploits exogenous variation in the expected profits and welfare created by the transport and subsidy treatments. We first explain our estimation approach and then the data variation used to identify each parameter.

Estimation Approach The probability that employer k from industry j chooses to hire applicant i over applicant i' in decision t is determined by the relative utility of hiring each applicant:

$$P_{kii't} = \Pr(u_{kit} > u_{ki't}) = \frac{exp(v_{kit})}{exp(v_{kit}) + exp(v_{ki't})}, \tag{6}$$

where v_{kit} is the utility of employer k from hiring applicant i in decision t in equation 5. We estimate $(\beta_j, d_j, \sigma^d_j, \alpha_{jm}, \sigma^\alpha_{jm}, \alpha_{jf}, \sigma^\alpha_{jf})$ within each industry j using a simulated maximum likelihood estimator (see appendix B.7.2). We control for employer industry fixed effects and a vector of applicant characteristics (Excel screening score, education, work experience, and marital status). We present results in money-metric utility (to the employer) by dividing the estimated preference parameters by β_j and bootstrap standard errors (Train and Weeks, 2005).

Identifying Variation We identify the parameters in equation 5 by estimating how hiring responds to the applicant's gender and the employers' expected profits, Π_{kit}, and welfare, $\mathcal{W}^E_{kit}$. We measure hiring in response to Π_{kit} and $\mathcal{W}^E_{kit}$ as opposed to the random employer and worker subsidies as paternalistic employers may not react to the worker subsidies as shown in section 4.3. We calculate employers' profit and welfare expectations using the predictions from the *Hiring* employers for the four applicants for which employers made both predictions and hiring choices (section 4.1, steps 2 and 4). First, we calculate Π_{kit} as the difference between the expected revenue generated by the worker and the wage paid to the worker. The expected revenue is the sum of the employers' base pay of BDT 500 (USD 5) and a piece rate of BDT 5 (USD 0.05) multiplied with the predicted number of tasks completed (the incentivized expected show-up rate multiplied by the incentivized expected conditional number of tasks completed; see section 4.1, step 2). The wage paid by the employer is randomly assigned based on the subsidy treatment: Employers in the *No Subsidy*, *Male Subsidy* and *Female Subsidy* treatments pay a wage of BDT 0 for both male and female workers; employers in the *Employer Subsidy* treatment pay a wage of BDT 0 for male workers, and of BDT -1,000 for female workers.

Second, we calculate $\mathcal{W}^E_{kit}$ as the difference between the wage offered to the worker and the job costs, $u^E_g(c^E_{kit})$. The wage paid to the worker is randomly assigned based on the subsidy treatment: workers in the *No Subsidy* and *Employer Subsidy* treatments receive BDT 1,500 (USD 15), while male and female workers in the *Male Subsidy* and *Female Subsidy* receive BDT 2,500 (USD 25), respectively. The expected job costs are the predicted job costs on a scale of 0–10 (see section 4.1, step 4) converted to money-metric using conversion rates calculated from employers' hiring responses to increases in costs and worker wages (described in appendix section B.7.1).[39]

If equation 5 correctly specifies employers' utility function and employers do not misreport productivity and cost beliefs to hide taste-based discrimination, then d_k measures employers' unbiased preference for hiring women relative to men. Neither predicted productivity nor costs differ between *Hiring* and *Prediction-Only* employers (see section 4.1, step 2, and appendix table C.4), alleviating concerns that employers may try to hide taste-based behind statistical or paternalistic concerns by understating productivity or overstating costs. We also show robustness without controlling for applicant characteristics or employer industry fixed effects, as well as by using a control function approach to adjust for misreporting of productivity and cost beliefs (described in appendix section B.7.3) and by estimating β_j and α_{kg} in equations 5 and 6 using only the random variation created by the employer and worker subsidies.

Results Our estimates of other-regarding preferences (α_{kg}) imply that employers internalize 11% of every BDT paid to male workers and 17% of every BDT paid to female workers (table 5). Employers in manufacturing place a significantly larger weight on women than men (p=0.03). Overall, our estimated welfare weights are slightly lower than those estimated by Chen and Li (2009) in dictator games (0.32–0.47). Consistent with our reduced form heterogeneity results in section 4.3, we observe some heterogeneity in other-regarding preferences towards female workers (σ^α_f), even though statistically insignificant.

We observe negative but insignificant taste for hiring women relative to men (d_k), which is consistent with findings that taste likely accounts for only a small amount of total labor market discrimination, and even this small amount may in fact be inaccurate statistical discrimination (List, 2004; Gneezy et al., 2012; Ewens et al., 2014; Bryson and Chevalier, 2015; Bohren et al., 2023; Chan, 2022). In South Asia, previous research has found little evidence of taste-based discrimination in the labor market (Ghani et al., 2016; Islam et al., 2023).

Results are robust to removing controls, using a control function approach (described in appendix B.7.3), and estimating equations 5 and 6 using the random employer and worker

[39]We also elicited costs in monetary terms directly with higher monetary values representing higher costs. However, we use the directly elicited costs, as the enumerators reported that respondents associated more money with better jobs and thus reported lower monetary values for costly jobs.

subsidies only, and simple logit or probit (appendix figure C.10).

Table 5: Employer Preferences: Parameter Estimates

	Pooled		Manufacturing		Services		Education	
	μ	σ	μ	σ	μ	σ	μ	σ
d	-0.109	0.000	-0.021	0.000	-0.054	0.000	-0.195	0.000
	(0.081)	(0.033)	(0.131)	(0.071)	(0.504)	(0.001)	(0.110)	(0.040)
α_m	0.112**	0.000	0.015	0.000	0.271	0.000	0.113*	0.000
	(0.056)	(0.017)	(0.089)	(0.099)	(0.893)	(0.048)	(0.079)	(0.010)
α_f	0.169***	0.018	0.173***	0.000	0.242	0.099	0.148**	0.172*
	(0.044)	(0.075)	(0.065)	(0.032)	(1.531)	(0.224)	(0.069)	(0.105)
p-value($\alpha_m = \alpha_f$)	0.233	.	0.033	.	0.834	.	0.592	.
Observations	1,826	.	610	.	592	.	624	.

Notes: The table presents parameter estimates from equation 5 estimated among all mixed-gender hiring pairs. All estimates in money metric. d in '000 BDT. Standard errors are calculated using 1,500 bootstrap samples. We cluster at the employer level and retain only those samples where the estimation routine converged within 50 iterations. We present p-values from testing whether α_m is statististically different from α_f.

6.1.3 Predicting Employer Beliefs as a Function of Wage and Transport

To endogenize selection and productivity, which were held constant in the experiment, we estimate the functions $\Pi_{jg}(w_{jg}, NT_{jg})$ and $\mathcal{W}^E_{jg}(w_{jg}, NT_{jg})$, which indicate how beliefs of industry j employers about profits and welfare for gender g workers form in equilibrium when selection and productivity vary with wages and transport. We assume that beliefs are invariant to hiring order and estimate average beliefs per industry (and thus drop indices t and k). We again first explain our estimation approach and then the identifying variation.

Estimation Approach We estimate how welfare and profit beliefs vary with employer and applicant characteristics as well as wages and information about the transport using a random forest model in the sample of *Beliefs-Elicitation* employers who did not make hiring decisions (see section 4.4). We then predict beliefs out-of-sample in the sample of *Hiring* employers (see appendix section B.7.4 for additional detail). That is, we answer the question "What would the *Hiring* employers have thought about the applicant if we had allowed wages and information about the transport to affect selection and productivity?" We then calculate the average expected productivity and costs at every wage with and without transport.

Identifying Variation Each *Beliefs-Elicitation* employer made eight predictions about applicants from the application experiment. In addition to the information provided to *Hiring* employers for making predictions (applicant gender, Excel screening score, education, work experience, and marital status), these employers were also informed about each applicant's wage and transport condition and that the wage and transport could influence selection and productivity in the application experiment as applicants knew their wage and transport condition before applying to the shift.

6.1.4 Constructing the Labor Demand Curve

Finally, we use the estimated preferences and predicted beliefs from the previous two subsections to simulate labor demand separately with and without transport. We construct a labor demand curve that approximates our theoretical framework (equation 2). We assume that each market consists of 495 employers, and 495 male and 495 female applicants, as in the experimental set-up. Each employer chooses whether to demand (i) a male worker in the market for male labor and (ii) a female worker in the market for female labor. In each market, the employer's outside option to hire is not hiring and receiving zero taste, profit, and other-regarding utility. We thus assume that employers' preferences ($d_k, \beta_j, \alpha_{kg}$) and beliefs ($\Pi_{jg}, \mathcal{W}_{jg}^E$) are stable across hiring environments, i.e., when employers choose between one male and one female applicant or between one male or one female applicant and the outside option of not hiring. We discuss the simulation of the demand curve in appendix B.8.

We present results using two different estimates of Π_{jg} resulting from different piece rates. In the experiment, employers received a piece rate of BDT 5 (USD 0.05) per task in addition to a base profit of BDT 500 (USD 5, the experimental compensation for employers) at a wage of BDT 1,500 (USD 15). Our preferred estimate of Π_{jg} eliminates the BDT 500 base profit (which was necessary for ethical reasons) and calibrates a piece rate that matches the expected average profits with the expected average profits in the experiment: $\widehat{\Pi}_{jg} = (5 + \frac{2{,}000}{\text{average productivity}}) \times \text{tasks} - w_{jg}$ (employers expect a base profit of BDT 500 at a wage of BDT 1,500; the associated piece rate is BDT 62 or USD 0.6). We also show results using the effective payment scheme used in the experiment: $\widehat{\Pi}_{jg} = 2,000 + 5\widehat{Tasks}_{jg} - w_{jg}$ (employers expect a base profit of BDT 500 at a wage of BDT 1,500).

6.2 Labor Supply

We estimate the labor supply non-parametrically using the reservation wages elicited in the application experiment. We calculate the fraction of gender g labor willing to work at every wage w_{jg} and with and without transport $NT_{jg} \in \{0, 1\}$, i.e., the fraction of workers I_g of labor g for which $\mathcal{W}_i^A \geq 0$ according to equation 1 using the empirical CDF:

$$\widehat{L_g^S}(w_{jg}, NT_{jg}) = \frac{1}{I_g} \sum_i \mathbf{1}(\overline{w}_i(NT_{jg}) \leq w_{jg}) \tag{7}$$

6.3 Counterfactuals

We use the estimated preferences and beliefs to conduct three sets of counterfactual analyses. First, we estimate the equilibria with and without transport. Second, we evaluate the importance of paternalistic discrimination relative to other drivers of the gender gaps in employment and wages in the experimental setting, such as supply-side differences and other forms of discrimination. Third, we estimate the cost-effectiveness of counterfactual policies, namely, safe transport paid by the policymaker and employment subsidies. To estimate worker welfare, we use beliefs of both employers and applicants about job costs. We also estimate employer profits using the observed productivity of workers hired at different wages with and without transport in the application experiment.[40]

6.3.1 Equilibrium

Not offering transport to applicants reduces female employment by 16% and female wages by 22% (figure 6, we present results by industry and using the piece rate used in the experiment in appendix figures C.11 and C.12). In addition, it reduces male employment by 7% and male wages by 13%. The decrease in demand for male labor is explained by two facts: (i) male and female labor is separable in the production function, i.e., employers do not hire between one male and one female worker, (ii) employers believe male workers' expected productivity is lower without transport (they believe male workers are less likely to show up to the shift). The equilibrium wage equalizes supply and demand, and the equilibrium labor quantity is the labor quantity at this wage. To calculate the equilibria, we use employers' beliefs about welfare and profits instead of true welfare and profits because (i) true welfare is not observed, and (ii) as paternalistic employers may not update their beliefs if they rarely hire women. The latter is consistent with the large extensive margin effects observed in the experiment, i.e., employers completely stop hiring women without transport. Results are qualitatively similar when calculating the equilibrium wage as the wage that equalizes the expected supply of tasks using employers' predicted productivity beliefs. Consistent with prediction 5, equilibrium female wages (but not male wages) decrease even when holding constant selection and productivity across treatments (appendix figure C.13).

6.3.2 How Much of the Gender Gap is Due to Paternalistic Discrimination?

To benchmark the importance of paternalistic discrimination in explaining the gender employment and wage gaps without transport observed in the experiment, we consider a series of counterfactuals that one-by-one eliminate different gender disparities in equations 27 and 7:

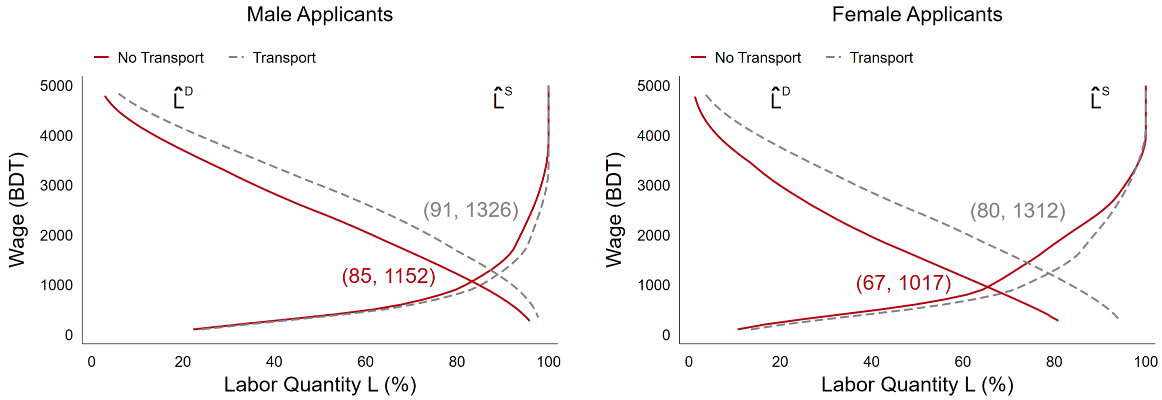
1. Paternalistic discrimination: We equalize (i) welfare weights ($\alpha_{kf} = \alpha_{km}$), (ii) expected welfare ($\mathcal{W}^E_{kf} = \mathcal{W}^E_{km}$), or (iii) both simultaneously ($\alpha_{kf}\mathcal{W}^E_{kf} = \alpha_{km}\mathcal{W}^E_{km}$).
2. Taste-based discrimination: We equalize non-pecuniary returns ($d_k = 0$).
3. Statistical discrimination: We equalize the expected profit at every wage $\left(\Pi^E_{kf} = \Pi^E_{km}\right)$.
4. Differences in labor supply: We equalize labor supply at every wage $L^S_f = L^S_m$). We rank both male and female applicants by their reservation wages and equate each female applicant's reservation wage with that of her male counterpart. We then recompute female

[40] See Bernheim and Taubinsky (2018) for a discussion of various approaches to behavioral welfare economics.

applicants' perceived welfare using these updated wages. We also update demand estimates to account for the changes in selection and its effects on employers' productivity and welfare beliefs (see also section 6.1.3).

We present results using our preferred profit measure (see section 6.1.4).

Figure 6: Equilibria in the Male and Female Labor Markets



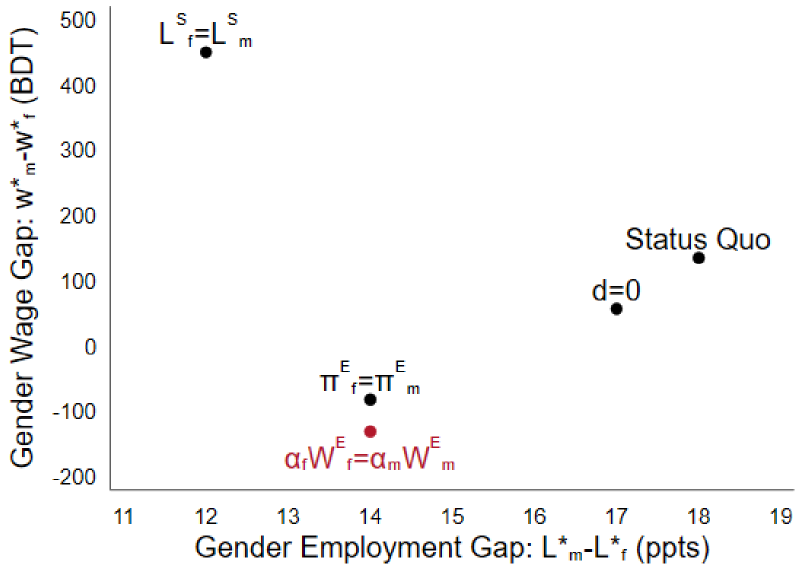
Notes: The graph shows the share of male and female workers demanded from equation 27 and the share of male and female workers supplied from equation 7 at each wage on a grid from 0 to 5,000 with and without transport. We use predicted productivity and cost beliefs from the *Beliefs-Elicitation* employers (see section 6.1.3) and calculate profits using a piece rate of BDT 62 (USD 0.6). Numbers in parentheses in the graph give (L_g^*, w_g^*). Numbers in gray on the right-top are the equilibrium with transport and numbers in red on the left-bottom are the equilibrium without transport.

Results Paternalistic discrimination driven by differences in beliefs about welfare rather than different welfare weights appears to be the most important source of gender employment and wage gaps in our experimental setting (figure 7). Eliminating paternalistic discrimination reduces the gender employment gap by 22% (4 ppts) and the gender wage gap by BDT 266 (USD 2.6, reversing the gender wage gap as male labor supply is higher than female labor supply). In addition, it increases worker welfare by 29% using workers' perception of worker welfare and by 5% using employers' perception of worker welfare (appendix table C.11). That is, paradoxically, also employers agree that female workers would be better off without paternalistic discrimination. This result is due to the fact that female workers would be hired at a higher wage (i.e., employers ask for a smaller wage discount from women). The effect of eliminating paternalistic discrimination seems almost entirely driven by differences in perceived welfare, as opposed to differences in the welfare weights placed on men and women.

By contrast, eliminating taste-based and statistical discrimination reduces the gender employment gap by 6% (1 ppts) and 22% (4 ppts) and the gender wage gap by BDT 78 (USD 0.8) and BDT 217 (USD 2), respectively, while eliminating differences in labor supply reduces the gender employment gap by 33% (6 ppts) but increases the gender wage gap (as the increase in female labor supply puts downward pressure on female wages). Note that paternalistic discrimination may be particularly prevalent in our experiment since the night shift is highly salient.

By contrast, differences in labor supply, as well as taste-based and statistical discrimination, might be relatively small as women who would never work do not participate in the experiment, and employers do not meet applicants in person and receive a highly informative signal of applicant quality (the Excel screening score).

Figure 7: Benchmarking Paternalistic Discrimination



Notes: The graph shows the gender employment gap $(L^*_m - L^*_f)$ and the gender wage gap $(w^*_m - w^*_f)$ of the status quo (the equilibrium in figure 6) as well as in four different counterfactuals that eliminate one-by-one (section 6.3.2): 1) paternalistic discrimination $\left(\alpha_f \mathcal{W}^E_f = \alpha_m \mathcal{W}^E_m\right)$, 2) taste-based discrimination $(d = 0)$, 3) statistical discrimination $\left(\Pi^E_f = \Pi^E_m\right)$, or 4) differences in labor supply $\left(L^S_f = L^S_m\right)$.

We also find that if employers made altruistic hiring choices ($\mathcal{W}^E_g = \mathcal{W}^{E:A}_g$) or used workers' perception of welfare ($\mathcal{W}^E_g = \mathcal{W}^A_g$), total experienced worker welfare would increase by 2-10% and 9-53% using employers' or workers' perception of worker welfare.

6.3.3 Counterfactual Policy Interventions

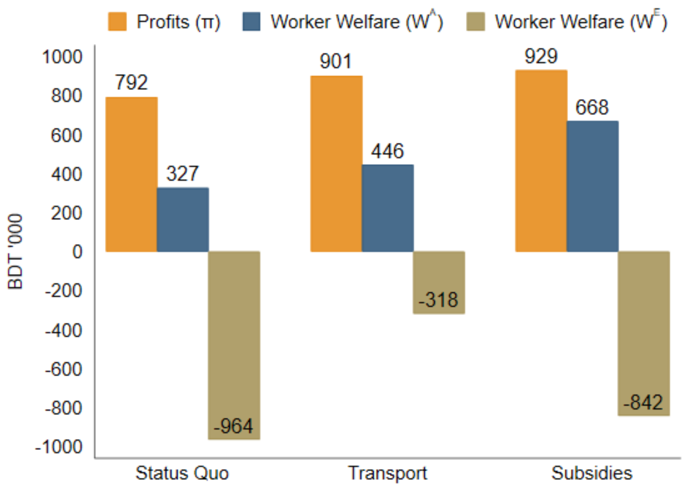
Finally, we consider the welfare effects and cost effectiveness of two counterfactual policies in our setting: safe transport for female workers and an employer subsidy for hiring women. We calculate the total profits of the 495 employers and the total worker welfare of the 990 workers (495 male and 495 female) in the market.

Safe Transport for Female Workers Based on the equilibria derived in section 6.3.2, we estimate the welfare effects and financial cost of providing safe transport to female workers. Hence, we consider the equilibrium with transport in the market for female labor and the equilibrium without transport in the market for male labor. The policymaker's expenditures are BDT 800 (USD 8) for each woman hired in equilibrium.

Female Subsidy We estimate the welfare effects of providing employers a subsidy s for hiring women. The labor supply at each wage w^E is given by all workers willing to work at the wage $w^A = w^E + s$. The labor demand at each wage w^E is given by employers' demand for workers willing to work at wage w^A when paying wage w^E. The equilibrium wage equalizes supply and demand and the equilibrium quantity is the labor quantity at the equilibrium wage. We evaluate the subsidy that equalizes the expenditures of the transport and subsidy interventions, amounting to BDT 900 (USD 9) per woman hired in equilibrium.

Results As compared to the hiring subsidies, the transport to female workers is more effective at reducing the gender employment gap (-72% versus -61%) but less effective at reducing the gender wage gap (-BDT 295, USD 3, versus -BDT 663, USD 7, appendix table C.13). The transport also results in smaller profit increases (BDT 109k, USD 2,000, versus BDT 137k, USD 1,370) and welfare increases using applicants' perception of welfare (BDT 119k, USD 1,120, versus BDT 341k, USD 3,410) but larger welfare increases using employers' perception of welfare (BDT 646k, USD 6,460, versus BDT 122k, USD 1,220, figure 8). At a cost of approximately BDT 330k (USD 3,300), the increases in profits and worker welfare from the hiring subsidies outweigh the implementation costs using both applicants' and employers' perceptions of welfare. The increases in profits and worker welfare from the transport outweigh the implementation costs under employers' perception of welfare but not applicants' perception of welfare.[41]

Figure 8: Welfare Effects of Transport and Subsidy Interventions



Notes: The graph shows total profits, total worker welfare (male + female worker welfare) using applicants' perceptions of worker welfare ($\mathcal{W}^A$) and employers' perceptions of worker welfare ($\mathcal{W}^E$) in three different equilibria: the status quo, in a counterfactual equilibrium in which female workers receive free transport and a counterfactual equilibrium in which female workers receive a subsidy of BDT 900 (USD 9). Results in BDT $'000$.

[41]Forcing employers to provide the transport themselves increases both the gender employment and wage gaps while reducing both profits and worker welfare, using both employers' and applicants' perceptions of worker welfare (appendix table C.13).

Whether safe transport or subsidies increase overall welfare more crucially depends on the relative accuracy of employers' and applicants' beliefs. Assuming that true experienced worker welfare is a convex combination of employers' and applicants' perception of worker welfare, $\mathcal{W}_g = \lambda\mathcal{W}_g^E + (1-\lambda)\mathcal{W}_g^A$, and summing the total worker welfare of male and female workers, employer profits, and costs to the implementers, the transport intervention increases welfare more for $\lambda \geq 0.29$. Thus, while subsidies have larger benefits than transport in terms of reducing the gender employment and wage gaps and increasing worker profits, the relative effects on worker welfare—and thus total welfare—depend on whether employers or applicants have more accurate beliefs about worker welfare. For example, when applicants underestimate the job costs because the employer-gender specific costs c_{kg} are high, transport interventions are more welfare-enhancing. But when employers overestimate the job costs because the worker-specific job costs c_i are low, subsidies are more welfare-enhancing.

7 Conclusion

This paper considers paternalism as a source of labor market discrimination. Combining a labor market model with data from two parallel field experiments, we document a high degree of paternalistic discrimination. A structural hiring model predicts that eliminating paternalistic discrimination reduces the gender employment gap by 22% and the gender wage gap by BDT 266 (USD 2.7) in our experimental setting.

Studying paternalistic discrimination offers valuable insights for policymakers aiming to affect labor market outcomes. For one, decreasing workers' job costs, both in the workplace or during the commute, or increasing workers' benefits may induce increases in both the supply of and demand for labor. Meanwhile, programs targeting supply-side changes—such as increasing women's qualifications in the workforce—may not translate into additional hiring if they fail to address demand-side constraints. Fundamentally, paternalistic discrimination is driven by the perception that one group faces larger costs from employment than another. If minority status in the workforce or in society itself generates costs to minorities, paternalistic discrimination may lead to a "minority trap" (Shan, 2022). That is, a disadvantaged group may not be hired because of the very costs related to being disadvantaged (for example, if employers believe a minority applicant will suffer ostracism), reinforcing the disadvantaged status.

Future research could explore how paternalism affects women's career trajectories or preferences over the long term, thus contributing to systemic discrimination (Bohren et al., 2022). Our data suggest that those who suffer the most from paternalistic discrimination are women with little experience. Obstacles to early-career employment may keep these applicants off the career ladder, slowing human capital accumulation and eliminating some future opportunities. While we focus on hiring decisions, other-regarding preferences may also lead to differential treatment in task assignment, promotion, or layoff decisions. Moreover, paternalistic discrimination might occur not only in the labor market but also inside the household (towards daughters) or in school (towards female students), thus differentially shaping the preferences of girls and boys during their most formative stages. Understanding these issues can enhance our understanding of gender differences in and outside the labor market and our analysis of available policies.

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A Theory Appendix

A.1 Production Function

We make several assumptions about the production function to ensure a unique solution to the employer's problem:

1. $Y^E(L_{kf}, L_{km})$ is a non-negative, continuously differentiable function with existing second derivatives.
2. $\lim\limits_{L_{kg}\to 0^+} \dfrac{\partial Y^E(L_{kf}, L_{km})}{\partial L_{kg}} \to \infty.$
3. $\frac{\partial^2 Y^E(L_{kf},L_{km})}{\partial L_{kf}^2} < 0$ and $\frac{\partial^2 Y^E(L_{kf},L_{km})}{\partial L_{km}^2} < 0$ for all L_{kf}, L_{km}.
4. $\frac{\partial^2 Y^E(L_{kf},L_{km})}{\partial L_{kf}^2} \frac{\partial^2 Y^E(L_{kf},L_{km})}{\partial L_{km}^2} > \left(\frac{\partial^2 Y^E(L_{kf},L_{km})}{\partial L_{km}\partial L_{kf}}\right)^2$ for all L_{kf}, L_{km}.

Assumption 2 ensures that each employer hires both men and women. Assumptions 3 and 4 ensure that the production function is concave. For example, the Cobb–Douglas production function satisfies these assumptions.

A.2 Derivation of Prediction 1

We derive prediction 1 in three steps: First, we derive the employers' expected change in worker welfare in response to increases in job costs c_g. Second, we derive the first-order conditions that describe the employers' problems. Third, we use the employers' expected change in worker welfare as well as the first-order conditions to derive the demand response to changes in job costs c_g.

First, we derive the change in welfare in response to increases in gender-specific costs c_g.

$$\frac{\partial \mathcal{W}_{kg}}{\partial c_g} = -\frac{\partial}{\partial c_g}\mathbb{E}_k[u_g(c_g + c_i + c_{kg})\,|\mathbb{E}_i[u_g^{E:A}(c_g + c_i + c_{kg})] \leq w_g], \tag{8}$$

for $u_g \in \{u_g^E, u_g^{E:A}\}$.

Note that the above implies that a change in job costs has two effects: (i) *direct*: job costs increase, thereby reducing the employer's perception of applicant utility, and (ii) *selection*: workers with smaller individual job costs self-select into the job, thereby partially offsetting the increase in perceived job costs. Without selection effect, for example, when employers engage in *selection neglect*, i.e., they do not consider how changing job costs changes the selection of workers, $\frac{\partial \mathcal{W}_{kg}}{\partial c_g} < 0$. As we make predictions for the experiment, we assume that selection is fixed going forward, i.e., that $\frac{\partial \mathcal{W}_{kg}}{\partial c_g} < 0$ and equal to the direct effect.

Second, we pin down the labor demand using the first-order conditions implied by the employer's problem (equation 2).

$$\underset{L_{kf}}{FOC} \quad d_{kf} + \frac{\partial Y^E(L_{kf}, L_{km})}{\partial L_{kf}} + \alpha_{kf}\mathcal{W}_{kf} - w_f = 0 \tag{9}$$
$$\underset{L_{km}}{FOC} \quad d_{km} + \frac{\partial Y^E(L_{kf}, L_{km})}{\partial L_{km}} + \alpha_{km}\mathcal{W}_{km} - w_m = 0.$$

Given assumptions 1–4 about the shape of the production function, the above system of equations has a unique maximum. Note that the employer hires until the utility contributed by the marginal worker is equal to the wage.

Third, implicit differentiation of the first-order conditions yields the following comparative static:

$$\frac{\partial L_{kf}}{\partial c_f} = -\frac{\alpha_{kf}\overbrace{\frac{\partial \mathcal{W}_{kf}}{\partial c_f}}^{<0}\overbrace{\frac{\partial^2 Y^E}{\partial L_{km}^2}}^{<0}}{\underbrace{\frac{\partial^2 Y^E}{\partial L_{kf}^2}\frac{\partial^2 Y^E}{\partial L_{km}^2} - \left(\frac{\partial^2 Y^E}{\partial L_{km}\partial L_{kf}}\right)^2}_{>0}} \tag{10}$$

This is $= 0$ if and only if $\alpha_{kf} = 0$, > 0 if and only if $\alpha_{kf} < 0$ and < 0 if and only if $\alpha_{kf} > 0$. The results are equivalent when considering $\frac{\partial L_{km}}{\partial c_m}$.

A.3 Derivation of Prediction 2

Assume that a job has an amenity that changes neither selection, nor expected productivity, and that reduces job costs by r and is priced at s. The worker can receive the job either with the amenity or with a monetary subsidy s.

The worker's expected welfare is $w_g - \mathbb{E}_i[u_g^A(c_{igk} - r)]$ with the amenity and $w_g + s - \mathbb{E}_i[u_g^A(c_{igk})]$ without the amenity. Assume the worker receives the job without the amenity. The worker will purchase the amenity to receive welfare $w_g + \mathbb{E}_i[u_g^A(c_{igk} - r)] \geq w_g + s - \mathbb{E}_i[u_g^A(c_{igk})]$ if and only if $s \leq \mathbb{E}_i[u_g^A(c_{igk}) - u_g^A(c_{igk} - r)]$. If $s > \mathbb{E}_i[u_g^A(c_{igk}) - u_g^A(c_{igk})]$, then the worker will not purchase the amenity and receive welfare $w_g + s - \mathbb{E}_i[u_g^A(c_{igk})] > w_g - \mathbb{E}_i[u_g^A(c_{igk} - r)]$. Thus, either way, the worker receives welfare $\geq w_g - \mathbb{E}_i[u_g^A(c_{igk} - r)]$.

Therefore, for the altruistic employer, $w_g + s - \mathbb{E}_k[\mathbb{E}_i[u_g^{E:A}(c_{igk})]] \geq w_g - \mathbb{E}_k[\mathbb{E}_i[u_g^{E:A}(c_{igk} - r)]]$ and labor demand for gender g labor should be weakly larger with subsidy and without amenity than without subsidy and amenity.

If we observe that employers demand gender g labor less with the subsidy, then employers expect that workers under-estimate the job cost utility loss, $\mathbb{E}_k[u_g^E(c_{igk})] > \mathbb{E}_k[\mathbb{E}_i[u_g^{E:A}(c_{igk})]]$, such that $w_g + s - \mathbb{E}_k[\mathbb{E}_i[u_g^{E:A}(c_{igk})]] \geq w_g - \mathbb{E}_k[\mathbb{E}_i[u_g^{E:A}(c_{igk} - r)]]$ and $w_g + s - \mathbb{E}_k[u_g^E(c_{igk})] < w_g - \mathbb{E}_k[u_g^E(c_{igk} - r)]$. Thus, employers other-regarding utility is larger from a worker with amenity than a worker who has the option to purchase the amenity.

A.4 Derivation of Prediction 3

We derive prediction 3 in two steps: First, we derive the employers' expected change in worker welfare in response to increases in wages w_g. Second, we use the employers' expected change in worker welfare as well as the first-order conditions to derive the demand response to changes in wages w_g.

First, we derive the change in welfare in response to increases in gender-specific wages w_g.

$$\frac{\partial \mathcal{W}_{kg}}{\partial w_g} = 1 - \frac{\partial}{\partial w_g}\mathbb{E}_k[u_g(c_i + c_{kg} + c_g)|\mathbb{E}_i[u_g^{E:A}(c_i + c_{kg} + c_g)] \leq w_g], \tag{11}$$

for $u_g \in \{u_g^E, u_g^{E:A}\}$.

Wage affects the employer's view of worker welfare through two channels. First, a wage increase directly contributes to worker welfare; higher wages are more desirable. Second, a selection effect changes the composition of workers. In particular, when the wage increases, the higher wage attracts workers with higher worker-specific costs, resulting in a decrease in worker welfare. The relative size of the direct and selection effects depend on the levels of cost as well as the utility functions. Welfare is unambiguously increasing when holding selection fixed, or when employers engage in selection neglect.

As we make predictions for the experiment, we assume that selection is fixed going forward, i.e., that $\frac{\partial \mathcal{W}_{kg}}{\partial w_g} = 1$.

Second, implicit differentiation of the first-order conditions 9 yields the following comparative static:

$$\frac{\partial L_{kf}}{\partial w_f} = \frac{\overbrace{\frac{\partial^2 Y^E}{\partial L_{km}^2}}^{<0}(1 - \alpha_{kf})}{\underbrace{\frac{\partial^2 Y^E}{\partial L_{kf}^2}\frac{\partial^2 Y^E}{\partial L_{km}^2} - \left(\frac{\partial^2 Y^E}{\partial L_{km}\partial L_{kf}}\right)^2}_{>0}} \tag{12}$$

The above is ≥ 0 if and only if $\alpha_{kf} \geq 1$, i.e., when employers do not place a higher weight on the welfare of the worker than their own welfare.

A.5 Derivation of Prediction 4

Note that, if $\alpha_{kf} > 0$, then equations 10 and 12 are increasing in absolute value in α_{kf}.

A.6 Derivation of Prediction 5

We derive prediction 5 in three steps. First, we set-up the system of equations describing the equilibrium. Second, we show that this system of equations has a unique solution. Third, we show how the equilibrium labor quantity and wages respond to changes in gender-specific costs c_g.

First, we set up the system of equations describing the equilibrium. As we are interested in the equilibrium comparative statics, we replace the continuum of employers with one representative employer.

Let c_i follow distribution h_g^I, which is a continuously differentiable density function with no mass points. The labor supply of gender g labor is then given by the following equation:

$$L_g = L_g^S \equiv \int_i \mathbb{1}\left(\mathbb{E}_i[u^A(c_i + c_{kg} + c_g)] \leq w_g\right) h_g^I(c_i) dc_i \tag{13}$$

The system of equations given by 9 and 13 then describes the equilibrium.

Second, we show that the system of equations describing the equilibrium has a unique solution. It has a unique solution if it has continuous partial derivatives with respect to all endogenous and exogenous variables and the determinant of the Jacobian of the system of equations is non-zero. This Jacobian is given the by matrix on the left of the following equation:

$$\begin{bmatrix} 1 & 0 & -\frac{\partial L_f^S}{\partial w_f} & 0 \\ 0 & 1 & 0 & -\frac{\partial L_m^S}{\partial w_m} \\ \frac{\partial^2 Y^E}{\partial L_f^2} & \frac{\partial^2 Y^E}{\partial L_f \partial L_m} & -(1-\alpha_f) & 0 \\ \frac{\partial^2 Y^E}{\partial L_m \partial L_f} & \frac{\partial^2 Y^E}{\partial L_m^2} & 0 & -(1-\alpha_m) \end{bmatrix} \begin{bmatrix} \frac{\partial L_f^*}{\partial c_f} \\ \frac{\partial L_m^*}{\partial c_f} \\ \frac{\partial w_f^*}{\partial c_f} \\ \frac{\partial w_m^*}{\partial c_f} \end{bmatrix} = \begin{bmatrix} \frac{\partial L_f^S}{\partial c_f} \\ 0 \\ -\alpha_f \frac{\partial \mathcal{W}_f}{\partial c_f} \\ 0 \end{bmatrix} \tag{14}$$

The following equation gives the determinant of the Jacobian:

$$
\begin{aligned}
|J| = & \underbrace{\frac{\partial L_f^S}{\partial w_f}\frac{\partial L_m^S}{\partial w_m}\left(\frac{\partial^2 Y^E}{\partial L_f^2}\frac{\partial^2 Y^E}{\partial L_m^2} - \left(\frac{\partial^2 Y^E}{\partial L_f \partial L_m}\right)^2\right)}_{>0} \underbrace{-\frac{\partial L_f^S}{\partial w_f}\frac{\partial^2 Y^E}{\partial L_f^2}(1-\alpha_m)}_{>0} \\
& \underbrace{-\frac{\partial L_m^S}{\partial w_m}\frac{\partial^2 Y^E}{\partial L_m^2}(1-\alpha_f)}_{>0} \underbrace{+(1-\alpha_f)(1-\alpha_m)}_{>0} \\
= & \left(\frac{\partial^2 Y^E}{\partial L_f^2}\frac{\partial L_f^S}{\partial w_f} - (1-\alpha_f)\right)\left(\frac{\partial^2 Y^E}{\partial L_m^2}\frac{\partial L_m^S}{\partial w_m} - (1-\alpha_m)\right) \\
& - \left(\frac{\partial^2 Y^E}{\partial L_f \partial L_m}\right)^2 \frac{\partial L_f^S}{\partial w_f}\frac{\partial L_m^S}{\partial w_m} > 0
\end{aligned}
$$

As the Jacobian is positive, the system of equation has a unique solution.

Next, we show how the equilibrium labor quantity and wages respond to changes in gender-specific costs c_g. By Cramer's rule, the aggregate solution can be expressed as

$$
\frac{\partial L_f^*}{\partial c_f} = \frac{|J_1|}{|J|} \qquad \frac{\partial L_m^*}{\partial c_f} = \frac{|J_2|}{|J|}
$$

$$
\frac{\partial w_f^*}{\partial c_f} = \frac{|J_3|}{|J|} \qquad \frac{\partial w_m^*}{\partial c_f} = \frac{|J_4|}{|J|}.
$$

Here $|J_j|$ is the matrix resulting from replacing the jth column of the Jacobian matrix with the solution to the system of equations. To ease notation, define $\frac{\partial L_g^D}{\partial w_g} = -(1-\alpha_g)$ and $\frac{\partial L_g^D}{\partial c_g} = -\alpha_g \frac{\partial \mathcal{W}_g}{\partial c_g}$. Calculating $\frac{|J_1|}{|J|}$ and re-arranging:

$$
\frac{\partial L_f^*}{\partial c_f} = \frac{|J_1|}{|J|} = \frac{\overbrace{\left(\frac{\partial L_f^S}{\partial c_f}\frac{\partial L_f^D}{\partial w_f} - \frac{\partial L_f^D}{\partial c_f}\frac{\partial L_f^S}{\partial w_f}\right)}^{>0}\overbrace{\left(\left(1 - \frac{\left(\frac{\partial^2 Y^E}{\partial L_m \partial L_f}\right)^2}{\frac{\partial^2 Y^E}{\partial L_f^2}\frac{\partial^2 Y^E}{\partial L_m^2}}\right)\frac{\partial L_m^D}{\partial w_m} - \frac{\partial L_m^S}{\partial w_m}\right)}^{<0}}{\underbrace{\frac{|J|}{\frac{\partial^2 Y^E}{\partial L_f^2}\frac{\partial^2 Y^E}{\partial L_m^2} - \left(\frac{\partial^2 Y^E}{\partial L_m \partial L_f}\right)^2}}_{>0}} < 0
$$

Define

$$
\delta \equiv \frac{\left(\frac{\partial^2 Y^E}{\partial L_m \partial L_f}\right)^2}{\frac{\partial^2 Y^E}{\partial L_f^2}\frac{\partial^2 Y^E}{\partial L_m^2}} \in [0,1) \tag{15}
$$

as the measure of the relative curvature across versus within gender. δ is increasing in the relatedness of male and female labor. Then:

$$\frac{\partial L_f^*}{\partial c_f} = \frac{\overbrace{\left(\frac{\partial L_f^S}{\partial c_f}\frac{\partial L_f^D}{\partial w_f} - \frac{\partial L_f^D}{\partial c_f}\frac{\partial L_f^S}{\partial w_f}\right)}^{>0}\overbrace{\left((1-\delta)\frac{\partial L_m^D}{\partial w_m} - \frac{\partial L_m^S}{\partial w_m}\right)}^{<0}}{\frac{|J|}{\underbrace{\frac{\partial^2 Y^E}{\partial L_f^2}\frac{\partial^2 Y^E}{\partial L_m^2} - \left(\frac{\partial^2 Y^E}{\partial L_m \partial L_f}\right)^2}_{>0}}} < 0$$

An increase in costs to female labor reduces the equilibrium quantity of women hired by reducing both female labor supply and demand for female labor. The magnitude of the shift depends on both the responsiveness of demand and supply to costs and wages. Note that the above is true for any $\alpha_f \in [0,1]$, implying that the equilibrium female labor quantity is decreasing in costs to female labor in a model with and without other-regarding preferences.

The results are equivalent when considering $\frac{\partial L_m^*}{\partial c_m}$.

Calculating $\frac{|J_3|}{|J|}$ and re-arranging:

$$\frac{\partial w_f^*}{\partial c_f} = \frac{|J_3|}{|J|} = \frac{\overbrace{\frac{\partial L_f^S}{\partial c_f}\left(\frac{\partial L_m^D}{\partial w_m} - \frac{\partial L_m^S}{\partial w_m}\right)}^{>0} - \overbrace{\frac{\partial L_f^D}{\partial c_f}\left((1-\delta)\frac{\partial L_m^D}{\partial w_m} - \frac{\partial L_m^S}{\partial w_m}\right)}^{<0}}{\frac{|J|}{\underbrace{\frac{\partial^2 Y^E}{\partial L_f^2}\frac{\partial^2 Y^E}{\partial L_m^2} - \left(\frac{\partial^2 Y^E}{\partial L_m \partial L_f}\right)^2}_{>0}}}$$

Thus, the equilibrium effect depends on the relative size of the supply versus the demand shift. In particular, the female equilibrium wage increases if and only if:

$$r_{c_f} > \underbrace{1 - \frac{\delta}{1 + r_{w_m}}}_{\in(0,1]}, \tag{16}$$

where $r_{c_f} \equiv |\frac{\epsilon_{c_f}^S}{\epsilon_{c_f}^D}|$ and $r_{w_m} \equiv |\frac{\epsilon_{w_m}^S}{\epsilon_{w_m}^D}|$ are the ratios of the supply and demand elasticities with respect to female costs and male wages, respectively, and $\delta \in [0,1)$ is the measure or relative curvature across versus within gender defined in equation 15.

The female equilibrium wage increases if the elasticity of supply in response to costs is proportionally larger than the elasticity of demand. As the right-hand side is ≤ 1, the female equilibrium wage always increases if the cost elasticity of supply is greater than the cost elasticity of demand.

A.7 Prediction 6

We next evaluate how the equilibrium wage and quantity of the other gender respond to an increase in gender-specific costs. As gender-specific costs increase, employers substitute toward labor of the other gender if male and female workers are substitutes, as labor of the other gender is able to generate similar revenues at larger other-regarding utility. Note that this implies that the gender employment gap is unambiguously increasing in gender-specific costs if male and female workers are substitutes. We formalize this in the following auxiliary prediction:

Prediction 6 (Substitutability)**.** *Holding selection and productivity constant, the demand for labor of the opposite gender and wages of labor of the opposite gender are increasing in gender-specific costs to substitute labor and decreasing in gender-specific costs to complement labor.*

Proof We derive prediction 6 in three steps. First, we assess under which conditions male and female workers are substitutes, complements, or neither. Second, we derive how labor demand is changing in increases in gender-specific costs of the opposite gender. Third, we derive how equilibrium hiring and wages are changing in increases in gender-specific costs of the opposite gender.

First, to assess under which conditions male and female workers are substitutes, complements, or neither, we calculate the cross-wage elasticity of demand of male labor with respect to female wages. Male and female workers are substitutes if the cross-wage elasticity is positive, i.e., an increase in female wages increases the demand for male workers, complements if the cross-wage elasticity is negative, i.e., an increase in female wages decreases the demand for male workers, and unrelated if the cross-wage elasticity is 0.

$$\epsilon_{w_f,w_m} = \frac{w_f}{L_m^D}\frac{\partial L_m}{\partial w_f} = -\underbrace{\frac{w_f}{L_m}}_{<0}\frac{\overbrace{\frac{\partial^2 Y^E}{\partial L_m \partial L_f}}^{?}\overbrace{(1-\alpha_f)}^{>0}}{\underbrace{\frac{\partial^2 Y^E}{\partial L_f^2}\frac{\partial^2 Y^E}{\partial L_m^2} - \left(\frac{\partial^2 Y^E}{\partial L_m \partial L_f}\right)^2}_{>0}} \tag{17}$$

Thus, $\epsilon_{w_f,w_m} > 0$ if and only if $\frac{\partial^2 Y^E}{\partial L_m \partial L_f} < 0$, $\epsilon_{w_f,w_m} < 0$ if and only if $\frac{\partial^2 Y^E}{\partial L_m \partial L_f} > 0$ and $\epsilon_{w_f,w_m} = 0$ if and only if $\frac{\partial^2 Y^E}{\partial L_m \partial L_f} = 0$. That is, male and female workers are substitutes if and only if $\frac{\partial^2 Y^E}{\partial L_m \partial L_f} < 0$, complements if and only if $\frac{\partial^2 Y^E}{\partial L_m \partial L_f} > 0$, and unrelated if and only if $\frac{\partial^2 Y^E}{\partial L_m \partial L_f} = 0$.

Therefore, the demand for male workers is increasing in female wages if male and female workers are substitutes, decreasing if they are complements, and constant if they are unrelated. The change in the demand for male workers is decreasing in α_f.

Second, we derive how labor demand is changing in increases in gender-specific costs of the opposite gender.

$$\frac{\partial L_m}{\partial c_f} = \frac{\alpha_f \overbrace{\frac{\partial \mathcal{W}_f}{\partial c_f}}^{<0} \overbrace{\frac{\partial^2 Y^E}{\partial L_m \partial L_f}}^{?}}{\underbrace{\frac{\partial^2 Y^E}{\partial L_f^2} \frac{\partial^2 Y^E}{\partial L_m^2} - \left(\frac{\partial^2 Y^E}{\partial L_m \partial L_f}\right)^2}_{>0}}. \tag{18}$$

Assuming $\alpha_f \geq 0$, the above is 0 if $\alpha_f = 0$ or if $Y_{L_m,L_f} = 0$, i.e., male and female workers are unrelated. For $\alpha_f > 0$, it is < 0 if $Y_{L_m,L_f} > 0$, i.e., male and female workers are complements, and > 0 if $Y_{L_m,L_f} < 0$, i.e., male and female workers are substitutes. That is, as the costs to female workers increase, other-regarding employers hire more male workers if male and female workers are substitutes, and less male workers if they are complements. Note that the change in male hiring is increasing in α_f.

Note that equation 10 is increasing in magnitude in relatability between male and female labor and has a global minimum if men and women are unrelated. Intuitively, if male and female labor are substitutes, employers substitute towards male labor when the perceived costs to female labor increase. On the other hand, if male and female labor are complements, the demand for male labor decreases, thus increasing the wage for male labor and further suppressing the demand for female labor.

Third, we derive how equilibrium hiring and wages are changing in increases in gender-specific costs of the opposite gender. First, we calculate the change in equilibrium male hiring in response to an increase in gender-specific costs to female labor:

$$\frac{\partial L_m^*}{\partial c_f} = \frac{|J_2|}{|J|} = \frac{\frac{\overbrace{\left(\frac{\partial L_f}{\partial w_f}\frac{\partial L_f^S}{\partial c_f} - \frac{\partial L_f}{\partial c_f}\frac{\partial L_f^S}{\partial w_f}\right)}^{>0} \overbrace{\frac{\frac{\partial^2 Y^E}{\partial L_{kf} \partial L_m}}{\frac{\partial^2 Y^E}{\partial L_m^2}} \frac{\partial L_m^S}{\partial w_m}}^{?}}{|J|}}{\underbrace{\frac{\partial^2 Y^E}{\partial L_f^2}\frac{\partial^2 Y^E}{\partial L_m^2} - \left(\frac{\partial^2 Y^E}{\partial L_m \partial L_f}\right)^2}_{>0}}$$

The effect of an increase in costs to female labor depends on the substitutability of male and female worker. $\frac{\partial L_m^*}{\partial c_f} = 0$ iff male and female workers are unrelated, $\frac{\partial L_m^*}{\partial c_f} > 0$ iff male and female workers are substitutes and $\frac{\partial L_m^*}{\partial c_f} < 0$ iff male and female workers are complements. This is true for any $\alpha_f \in [0,1]$. The results are equivalent when considering $\frac{\partial L_f^*}{\partial c_m}$.

Finally, we calculate the change in equilibrium male wages in response to an increase in gender-specific costs to female labor:

$$\frac{\partial w_m^*}{\partial c_f} = \frac{|J_4|}{|J|} = \frac{\overbrace{\left(\frac{\partial L_f}{\partial w_f}\frac{\partial L_f^S}{\partial c_f} - \frac{\partial L_f}{\partial c_f}\frac{\partial L_f^S}{\partial w_f}\right)}^{>0}\overbrace{\frac{\frac{\partial^2 Y^E}{\partial L_f \partial L_m}}{\frac{\partial^2 Y^E}{\partial L_m^2}}}^{?}}{\frac{|J|}{\underbrace{\frac{\partial^2 Y^E}{\partial L_f^2}\frac{\partial^2 Y^E}{\partial L_m^2} - \left(\frac{\partial^2 Y^E}{\partial L_m \partial L_f}\right)^2}_{>0}}}$$

The effect of an increase in costs to female labor depends on the substitutability of male and female workers. $\frac{\partial w_m^*}{\partial c_f} = 0$ iff male and female workers are unrelated, $\frac{\partial w_m^*}{\partial c_f} > 0$ iff male and female workers are substitutes as the demand for male labor increases and $\frac{\partial w_m^*}{\partial c_f} < 0$ iff male and female workers are complements as the demand for male labor decreases. This is again true for any $\alpha_f \in [0,1]$. The results are equivalent when considering $\frac{\partial w_f^*}{\partial c_m}$.

A.8 Examples with CES and Cobb–Douglas Production Functions

To illustrate the mechanisms, we assume that the worker's utility function is linear and additive in wages and benefits and convex in job costs and that the production function is either constant elasticity of substitution or Cobb–Douglas.

A.8.1 CES Production Function

Assuming that the expected productivity of workers equals their real productivity in equilibrium, the production function of employers in industry j is:

$$Y^E(L_{kf}, L_{km}) = p\left(a_{jf}(\widehat{Y}_{jf}L_{kf})^\rho + a_{jm}(\widehat{Y}_{jm}L_{km})^\rho\right)^{\frac{\upsilon}{\rho}},$$

where p is the piece rate, $\widehat{Y}_{jf}$ and $\widehat{Y}_{jm}$ are the productivity of female and male workers in industry j, $\rho < 1$ is the substitution parameter, υ is the degree of homogeneity of the production function (where $\upsilon = 1$ is constant returns to scale, $\upsilon < 1$ is decreasing returns to scale, and $\upsilon > 1$ is increasing returns to scale) and a_{jf} and $a_{jm} = 1 - a_{jf}$ are the share parameters. The employer's utility from profits is β_j. In addition, the employer receives non-pecuniary benefits d_{kg} from hiring a worker of gender g, and internalizes fraction α_{kg} of the applicant's expected net on-the-job utility $\mathcal{W}_{kg}$.

The first-order conditions are:

$$\underset{L_{kg}}{FOC} \quad d_{kg} + \beta_j p a_{jf} \widehat{Y}_{jg}^{\rho} L_{kg}^{\rho-1} \upsilon (a_{jf}(\widehat{Y}_{jf} L_{kf})^{\rho} + a_{jm}(\widehat{Y}_{jm} L_{km})^{\rho})^{\frac{\upsilon-\rho}{\rho}} + \alpha_{kg}\mathcal{W}_{kg} - w_g = 0$$

Rearranging, we can solve for the labor g demand:

$$L_{kg} = \frac{(\beta_j p \upsilon)^{\frac{1}{1-\upsilon}} \left(\frac{a_{jg}\widehat{Y}_{jg}^{\rho}}{w_g - d_{kg} - \alpha_{kg}\mathcal{W}_{kg}} \right)^{\frac{1}{1-\rho}}}{\left(\sum_{g' \in \{f,m\}} \left(\frac{a_{jg'}\widehat{Y}_{jg'}^{\rho}}{(w_{g'} - d_{kg'} - \alpha_{kg'}\mathcal{W}_{kg'})^{\rho}} \right)^{\frac{1}{1-\rho}} \right)^{\frac{\rho-\upsilon}{\rho(1-\upsilon)}}}.$$

A.8.2 Cobb–Douglas Production Function

Let the production function of employers in industry j be given by:

$$Y^E(L_{kf}, L_{km}) = L_{kf}^{a_{jf}} L_{km}^{a_{jm}},$$

where a_{jf} and a_{jm} are the output elasticities of female and male workers, respectively. The employer's utility from profits is β_j.

The first-order conditions are:

$$\underset{L_{kg}}{FOC} \quad d_{kg} + \beta_j L_{kg}^{a_{jg}-1} L_{kg'}^{a_{jg'}} + \alpha_{kg}\mathcal{W}_{kg} - w_g = 0$$

Rearranging, we can solve for the labor g demand:

$$L_{kg} = \frac{w_{g'} - d_{kg'} - \alpha_{kg'}\mathcal{W}_{kg'}}{\beta_j^{\frac{1}{a_{jg'}}} (w_g - d_{kg} - \alpha_{kg}\mathcal{W}_{kg})^{1-\frac{1}{a_{kg'}}}}.$$

B Technical Appendix

B.1 Ethical Considerations

We took several steps to ensure the safety of all participants. First, we informed all participants about the experiment and obtained informed consent for participation, that is, in the classification system of Harrison and List (2004), we conducted a framed field experiment rather than a natural field experiment. This ensured that applicants could evaluate their risks before joining the study. Second, we calibrated the payments with input from our local partners to be sufficiently rewarding for the inconvenience of a night-shift job without being coercive (Ambuehl et al., 2022). Finally, to ensure that all night-shift workers in the experiment arrived home safely, we provided transport to all workers at the end of the shift through a private transportation firm with vetted drivers. Instead of randomizing the safety of the job, we randomized the perception of safety among employers as described in more detail in section 4. This allowed us to identify employers' responses to perceptions of safety without jeopardizing the actual safety of any applicants.

B.2 Information about Sample Industries

We recruit employers from three industries: Manufacturing, Retail & Services, and Education. These industries employ substantially different numbers of men and women, giving us the opportunity to test whether hiring behavior in the experiment reflects aspects of the employers' usual market. Urban workers in Retail & Services are 77% male, Manufacturing workers 61% male, and Education workers 53% male. We calculate the Retail & Services employment rate combining repair of wholesale and retail trade and repair of motor vehicles; accommodation and food service activities, activities of households as employers, and other service activities.

The gender wage gap is largest in Manufacturing, where men earn about BDT 4,200 more than women per month (USD 42; 14,570 for men vs. 10,346 for women). Male Services & Retail workers in urban areas earn about BDT 3800 more then their female counterparts (USD 38; BDT 14,131 for men vs. BDT 10,313 for women). In Education, men earn about BDT 3,200 more than women per month (USD 32; BDT 26,790 for men vs. 23,568 for women) BBS (2018).

B.3 Field Setup

Figure C.1: Applicant Recruitment Setup

Notes: The picture shows one of our applicant recruitment booths on a university campus.

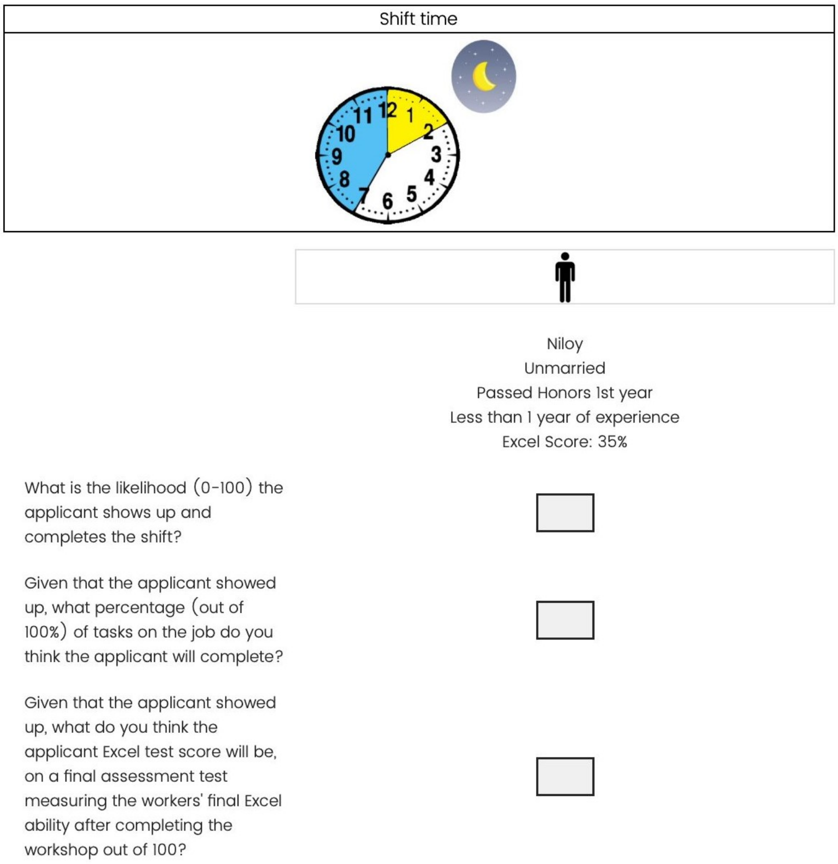
Figure C.2: Night-Shift Workshop and Job

Notes: The picture shows one of our night-shift workshops.

B.4 Experimental Interfaces

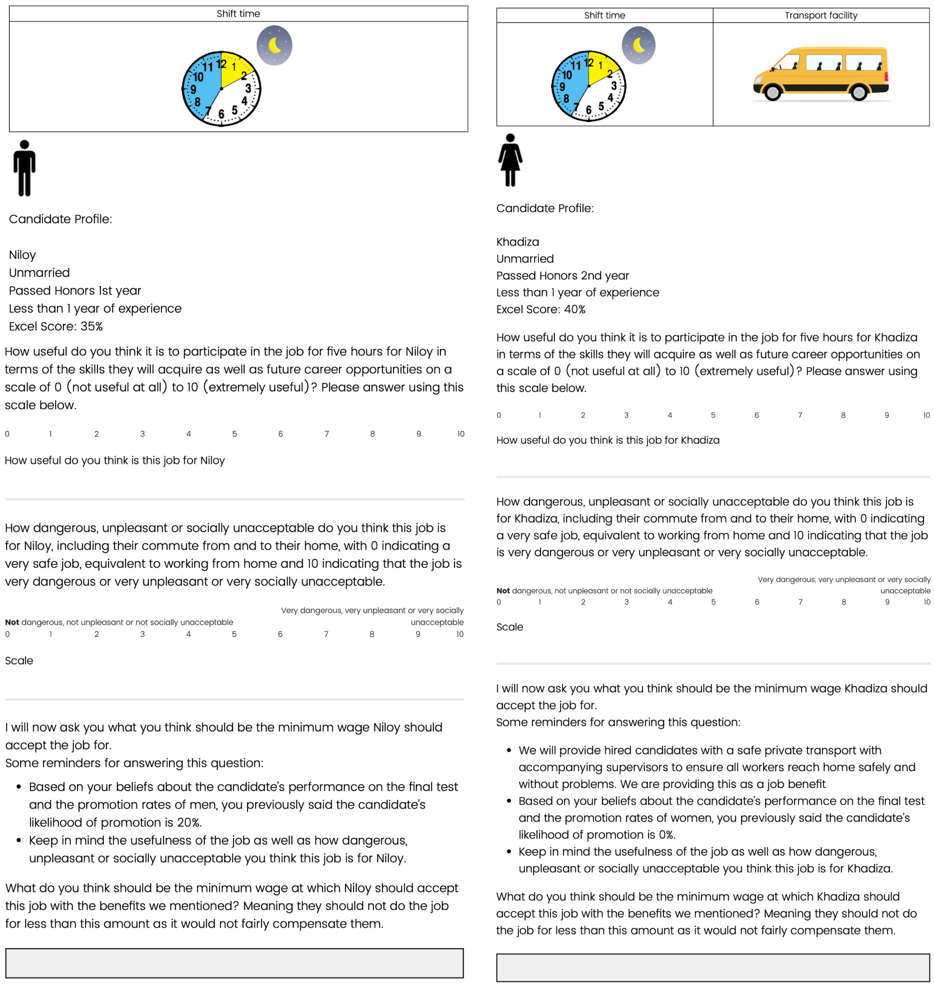
B.4.1 Hiring Experiment

Figure C.3: Experimental Interface to Make Productivity Predictions



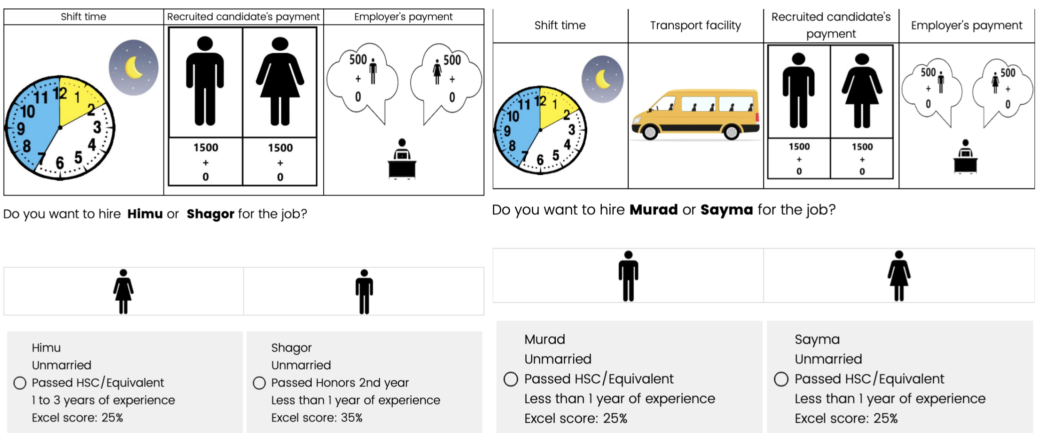
Notes: Translated from Bangla to English.

Figure C.4: Experimental Interface to Make Cost Predictions without (left) and with transport (right)



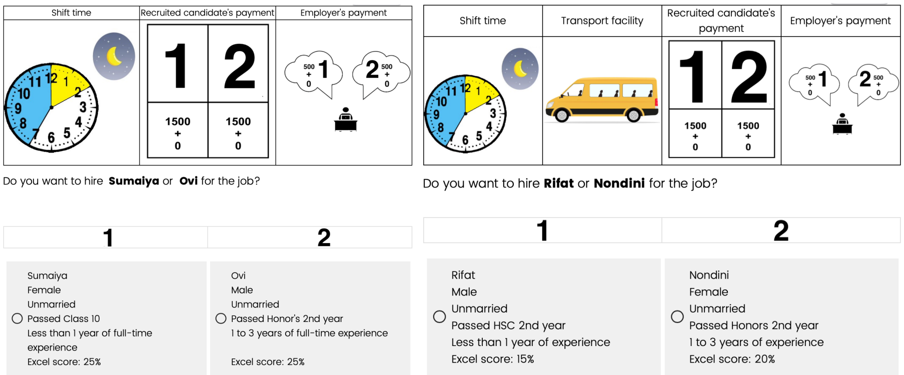
Notes: Translated from Bangla to English.

Figure C.5: Experimental Interface to Make Hiring Decisions without (left) and with transport (right)



Notes: Translated from Bangla to English.

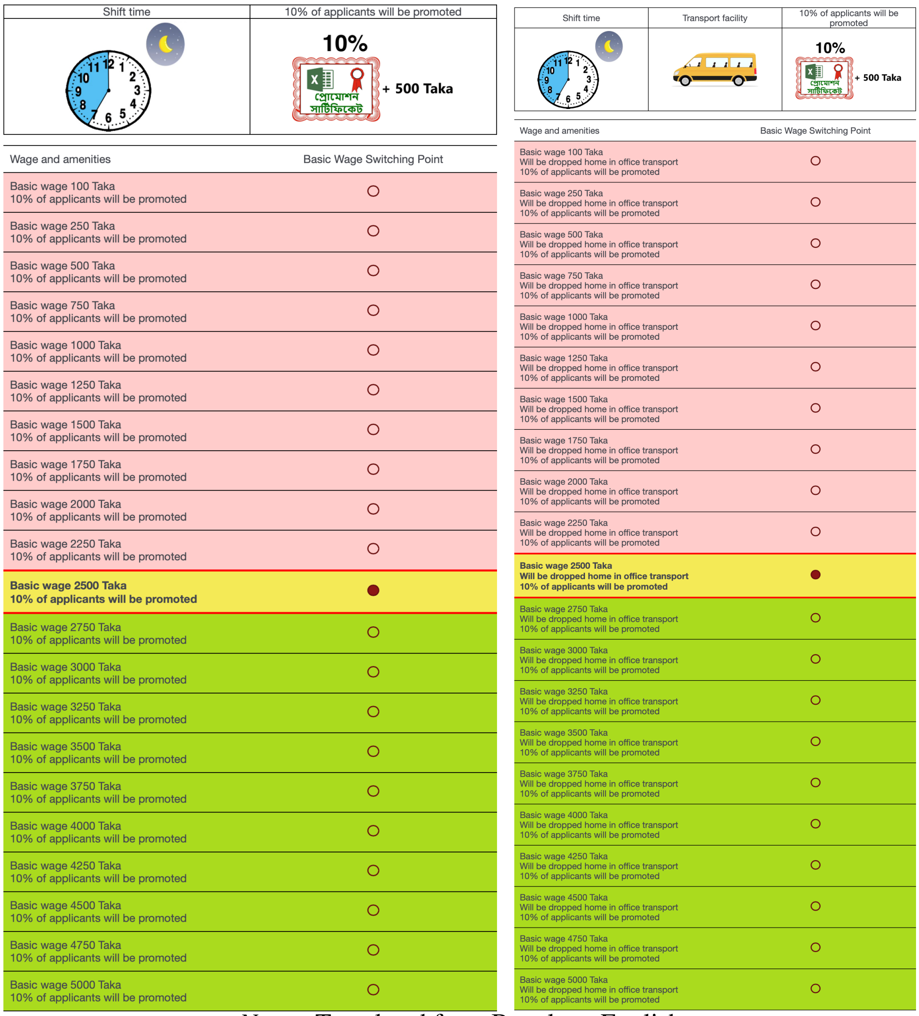
Figure C.6: Experimental Interface to Make Hiring Decisions without (left) and with transport (right) in the Candidate 1 versus Candidate 2 Setup



Notes: Translated from Bangla to English.

B.4.2 Application Experiment

Figure C.7: Experimental Interface to Elicit Reservation Wage Decisions without (left) and with transport (right)



Notes: Translated from Bangla to English.

B.5 Matching of Applicant Pairs in the Hiring Experiment

To mimic a realistic hiring process in which similar applicants apply for the same job, we randomly matched applicants with similar scores to each other using the following procedure. First, we ordered the 14 male and ten female workers by score. Second, we randomly matched two men from the bottom half with each other and two men from the top half. Third, we randomly matched the remaining top five men with the top five women and the remaining bottom five men with the bottom five women.

B.6 Survey Questions

B.6.1 Understanding Questions in the Hiring Experiment

1. What's the timing of the Excel workshop and job? a) 9 a.m.to 5 p.m.. b) 7 p.m. to 12 a.m.. c) 9 p.m. to 5 a.m..

2. *Transport*: When will the recruited workers learn about the safe transport? a) Before the shift. b) At the end of the shift. *No Transport*: When do workers learn that the Excel workshop and job takes place from 7 p.m. to 12 a.m.? a) They already learned when they applied for the job. b) Before the shift. c) At the end of the shift.

3. How much compensation do you receive per task your recruited worker completes? a) 3 Taka. b) 4 Taka. c) 5 Taka.

4. Based on the lottery, what is the bonus payment that you are going to receive? a) 0 Taka. b) 1,000 Taka if the recruited worker is male. c) 1,000 Taka if the recruited worker is female.

5. Based on the lottery, what is the bonus payment that the recruited worker will receive? a) 0 Taka. b) 1,000 Taka if the recruited worker is male. c) 1,000 Taka if the recruited worker is female.

B.6.2 Understanding Questions in the Application Experiment

1. What's the timing of the Excel workshop and job? a) 9 a.m.to 5 p.m.. b) 7 p.m. to 12 a.m.. c) 9 p.m. to 5 a.m..

2. For the job and amenities that you are eligible for, which of the following is true? a) Most applicants do not receive a promotion premium and a promotion certificate. b) Most applicants receive a promotion premium and a promotion certificate. c) Some applicants will receive a promotion premium, and other applicants will receive a promotion certificate.

3. If someone is offered a job with a benefit that they like, then how would the minimum wage at which they would accept the job change? a) It would increase. b) It would decrease. c) It would not change.

B.7 Structural Estimation

B.7.1 Calculating the Cost Conversion Rate

First, we estimate equation 3 replacing the *No Transport* indicator with the predicted costs for the female and male workers compared in each pair. We also replace the applicant fixed effects with the worker characteristics shown to the employer as we only have two male and female cost predictions per employer. Second, we calculate the conversion factors as the coefficients on the costs for men or women divided by the coefficients on the male and female subsidies from equation 3, multiplied by -1,000.

B.7.2 Simulated Maximum Likelihood

We compute the unconditional choice probability by integrating over the mixing distribution. Thus, the unconditional likelihood of each employer k making the observed sequence of choices is

$$\mathscr{L}(d_k, \beta_j, \alpha_{kf}, \alpha_{km}) = \prod_k \prod_t \prod_i \prod_{i' \neq i} \left(\int P_{kii't} f(d_k, \alpha_{kf}, \alpha_{km}) d(d_k, \beta_j, \alpha_{kf}, \alpha_{km}) \right)^{H_{kii't}}, \tag{19}$$

where $H_{kii't}$ is an indicator that is 1 if employer k hires applicant i over i' in hiring choice t and $f(d_k, \beta_j, \alpha_{kf}, \alpha_{km})$ is the density of the random parameters. We estimate

Taking the log of equation 19, we get the log-likelihood function:

$$log\mathscr{L} = \sum_k \sum_t \sum_i \sum_{i' \neq i} H_{kii't} \ln \left(\int P_{kii't} f(d_k, \alpha_{kf}, \alpha_{km}) d(d_k, \alpha_{kf}, \alpha_{km}) \right).$$

Given the complexity of the integral, we simulate the unconditional probabilities by drawing $(d_k, \alpha_{kf}, \alpha_{km})^m$ from $f(d_k, \alpha_{kf}, \alpha_{km})$ M times:

$$\hat{P}_{kii't} = \frac{1}{M} \sum_{m=1}^{M} P^m_{kii't},$$

where $P^m_{kii't}$ denotes the probability that is generated by plugging $(d_k, \alpha_{kf}, \alpha_{km})^m$ into $P_{kii't}$.

To estimate our parameters, we then maximize the simulated log likelihood (SLL) function

$$SLL = \sum_k \sum_t \sum_i \sum_{i' \neq i} H_{kii't} \ln \left(\hat{P}_{kii't} \right).$$

B.7.3 Control Function Approach

We would like to estimate the following equation:

$$v_{ik} + \varepsilon_{ik} = d_k + \beta_j \Pi_{ik} + \alpha_{g_i k} \mathcal{W}_{ik} + \varepsilon_{ik}. \tag{20}$$

Assume we do not observe the true profit and welfare beliefs because of measurement error or misreporting. Instead, we observe $\Pi^*_{ik} = \Pi_{ik} + \varepsilon^{\Pi}_{ik}$ and $\mathcal{W}^*_{ik} = \mathcal{W}_{ik} + \varepsilon^{\mathcal{W}}_{ik}$ (for example, employers with high social image concerns might report low profits or welfare whenever they do not hire women in order not to appear sexist). We can thus rewrite equation 20:

$$v_{ik} + \varepsilon_{ik} = d_k + \beta_j \Pi_{ik} + \alpha_{g_i k} \mathcal{W}_{ik} + \underbrace{\beta_j \varepsilon^{\Pi}_{ik} + \alpha_{g_i k} \varepsilon^{\mathcal{W}}_{ik}}_{\varepsilon^{end}_{ik}} + \varepsilon^{ex}_{ik}, \tag{21}$$

where ε^{end}_{ik} is correlated with Π_{ik} and $\mathcal{W}_{ik}$ and ε^{ex}_{ik} is neither correlated with $\mathcal{W}_{ik}$ nor Π_{ik}.

We adopt a two-step procedure similar to that developed by Rivers and Vuong (1988).[42] First, let

$$\Pi_{ik} = Z'_k \kappa^{\Pi}_j + X'_i \gamma^{\Pi}_j + \mu_j + \tilde{\varepsilon}^{\Pi}_{ik} \tag{22}$$

and

$$\mathcal{W}_{ik} = Z'_k \kappa^{\mathcal{W}}_j + X'_i \gamma^{\mathcal{W}}_j + \mu_j + \tilde{\varepsilon}^{\mathcal{W}}_{ik}, \tag{23}$$

where X_i is a vector of worker characteristics shown to the employer, i.e., the applicant's gender, Excel screening score, education, work experience, and marital status, μ_j are employer industry fixed effects, and Z_{ik} constitutes a vector of transport and subsidy treatment assignments, which are independent of X_i, μ_j, ε^{Π}_{ik}, $\varepsilon^{\mathcal{W}}_{ik}$, ε^{end}_{ik}, and ε^{ex}_{ik}. $\tilde{\varepsilon}^{\mathcal{W}}_{ik}$, $\tilde{\varepsilon}^{\Pi}_{ik}$, and ε^{end}_{ik} are jointly normal. We estimate equations 22 and 23 using OLS separately by industry.

Second, we plug the fitted residuals $\hat{\tilde{\varepsilon}}^{\Pi}_{ik}$ and $\hat{\tilde{\varepsilon}}^{\mathcal{W}}_{ik}$ (i.e., the endogenous parts of Π_{ik} and $\mathcal{W}_{ik}$ not explained by the random treatment assignments Z_k, applicant characteristics X_i or fixed effects μ_{jt} and μ_{enum}) into equation 20 and estimate the following random coefficients logit model:

$$v_{ik} + \varepsilon_{ik} = d_k + \beta_j \Pi_{ik} + \alpha_{g_i k} \mathcal{W}_{ik} + X_i \gamma + \mu_j + \delta^{\Pi} \hat{\tilde{\varepsilon}}^{\Pi}_{ik} + \delta^{\mathcal{W}} \hat{\tilde{\varepsilon}}^{\mathcal{W}}_{ik} + \tilde{\varepsilon}^{ex}_{ik}, \tag{24}$$

where $\tilde{\varepsilon}^{ex}_{ik} \sim EV1$ is the error term after controlling for the fitted residuals.

As expected, the employer subsidy increases the expected profit by approximately BDT 1,000 (USD 10) in equation 22 (table C.9). By contrast, the *No Transport* treatment reduces

[42] See also Villas-Boas and Winer (1999), Petrin and Train (2010), Wooldridge (2015) and Hahn and Ridder (2017).

the expected welfare by BDT 936 (USD 10) and BDT 1,734 (USD 17). At the same time, the male and female worker subsidies increase the expected welfare of male and female workers by approximately BDT 1,000 (USD 10) each.

The results from equation 24 suggest mismeasurement of reported profits and welfare only among employers in the education industry ($\widehat{\delta^{\Pi}} = 2.6$ $\widehat{\delta^{\mathcal{W}}} = -0.4$, table C.10).

B.7.4 Random Forest Algorithm

We use a random forest algorithm to predict out-of-sample employer beliefs about profits and welfare. The random forest algorithm avoids over-fitting given our relatively high number of independent variables and low number of observations (Breiman, 2001).[43] The algorithm operates on the principle of ensemble learning. Initially, N_1 subsets of the data are created by randomly selecting observations with replacement. Subsequently, individual decision trees are constructed for each of the subsets. Here, the random forest algorithm restricts the number of variables considered at each split (N_2) to a randomly selected subset, thereby introducing an additional layer of randomness. The resulting decision trees are then collectively applied to generate predictions. Since we use a regression model, the final predictions typically are the mean of the predictions across all trees.

We tune the hyperparameters N_1 and N_2 using a grid search. We try values between 25 and 1,000 in steps of 25 for N_1 and values between 1 and the number of independent values for N_2. We then select the combination of iterations and number of variables that creates the lowest out-of-bag (OOB) error and use those parameters for our final predictions.

The OOB error is measuring the prediction without the need for a separate test set. This allows us to utilize all of our experimental data for training the algorithm. As we mentioned above, in the random forest algorithm, each decision tree is trained on a different bootstrap sample of the original dataset. The data points from the original dataset that are not included in a given bootstrap sample are out-of-bag for the corresponding decision tree. After the random forest algorithm has been trained, we generate predictions for datapoints using the decision trees that were not trained on them. The resulting predictions are then compared with the actual target values for those data points to calculate the OOB error.

The main predictors of productivity are whether the job provides transport, the number of male employees the employer has, the employer's industry, and the worker's Excel screening score. The main predictors of perceived costs are whether the job provides transport, applicant gender, the employer's industry, and how many hiring choices the employer made in the last three years. The OOB root mean squared prediction errors are 11.8/100 and 0.66/10, respectively.

[43] We use the implementation in Stata by Schonlau and Zou (2020).

B.8 Demand Simulation

To estimate demand, we construct a large number (1,000) of simulated employers by drawing preference parameters from the estimated distributions and calculating the expected value of a male and female hire to each simulated employer at any given wage with and without transport:

$$\widehat{v_{kg}}(w_{jg}, NT_{jg}) = \widehat{d_k} + \widehat{\beta_j}\widehat{\Pi_{jg}}(w_g, NT_{jg}) + \widehat{\alpha_k}\widehat{\mathcal{W}^E_{jg}}(w_{jg}, NT_{jg}). \tag{25}$$

The probability that employer k in industry j hires a worker of gender g at wage w_{jg} with and without transport, $NT_{gj} \in \{0, 1\}$, is then given by:

$$\widehat{P_{kg}}(w_{jg}, NT_{jg}) = \Pr(\widehat{v_{kg}}(w_{jg}, NT_{jg}) + \Delta\eta_{kg} > 0) = \frac{exp(\widehat{v_{kg}}(w_{jg}, NT_{jg}))}{1 + exp(\widehat{v_{kg}}(w_{jg}, NT_{jg}))}, \tag{26}$$

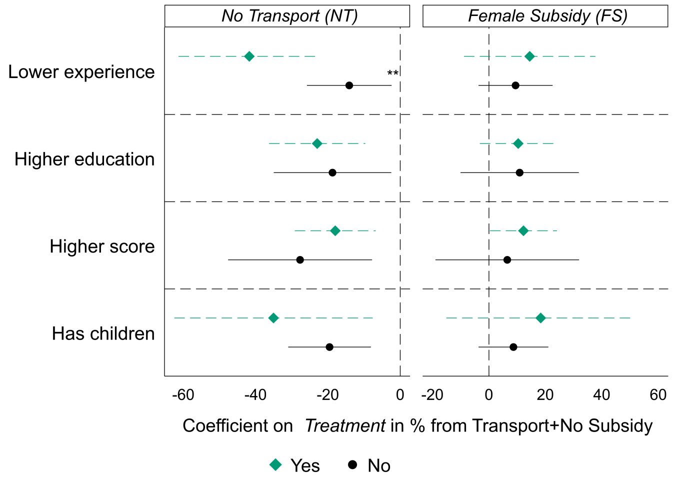
where $\Delta\eta_{kg} = \eta_{kg} - \eta_{k0} \sim \text{Logistic}(0, 1)$, with $\eta_{k0} \sim EV1$ being the unobserved demand shock of not hiring a worker. We then calculate the aggregate labor demand as the average hiring probability among the 1,000 simulated employers for the pool of applicants willing to work at each wage on a BDT-100 grid between 100 and 5,000 with and without transport.

$$\widehat{L^D_g}(w_{jg}, NT_{jg}) = \frac{1}{1,000}\sum_k \widehat{P_{kg}}(w_{jg}, NT_{jg}). \tag{27}$$

C Empirical Appendix

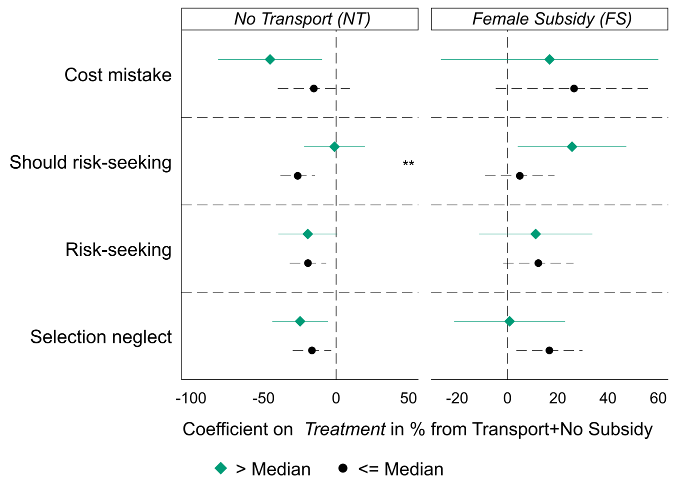
C.1 Figures

Figure C.8: Hiring by Transport and Female Subsidy Information and Applicant Characteristics



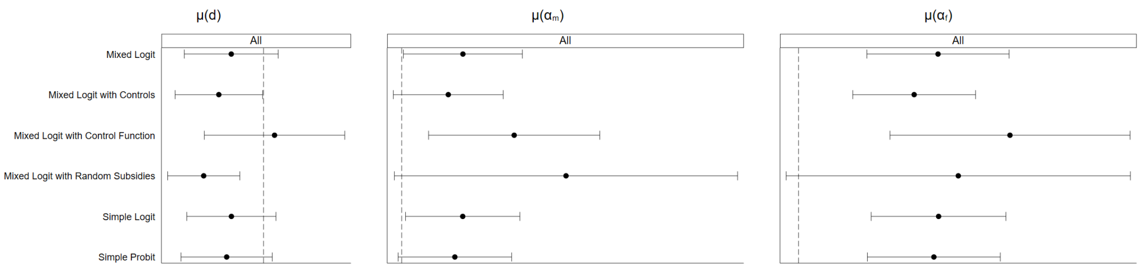
Notes: The graphs show the coefficients on the *No Transport* and the *Female Subsidy* indicators from regression 3 run separately among employers without subsidy (on the left) and with transport (on the right). We run the regressions in different subsets of applicant pairs. We compare pairs in which the female applicant has less work experience, higher education, or a higher Excel score than the male applicant versus pairs in which the woman has the same or more work experience, the same or less education, or the same or a lower Excel score as well as pairs in which the female applicant has children versus pairs in which she does not. Asterisks from comparing the coefficients across subsamples. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Figure C.9: Hiring by Transport and Female Subsidy Information and Employer Characteristics



Notes: The graphs show the coefficients on the *No Transport* and the *Female Subsidy* indicators from regression 3 run separately among employers without subsidy (on the left) and with transport (on the right). We run the regressions in different subsets of employers (see section 4.2). Asterisks from comparing the coefficients across subsamples. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

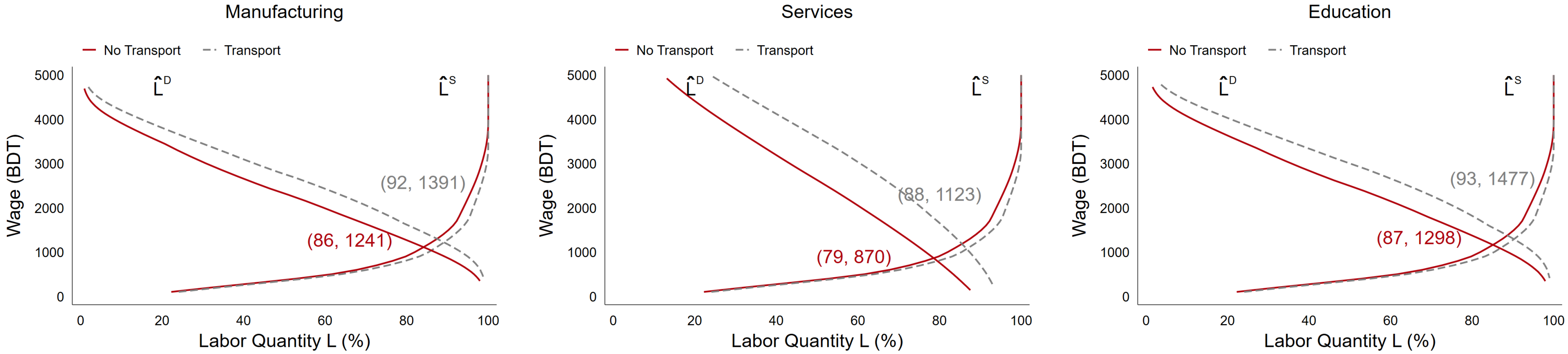
Figure C.10: Parameter Robustness



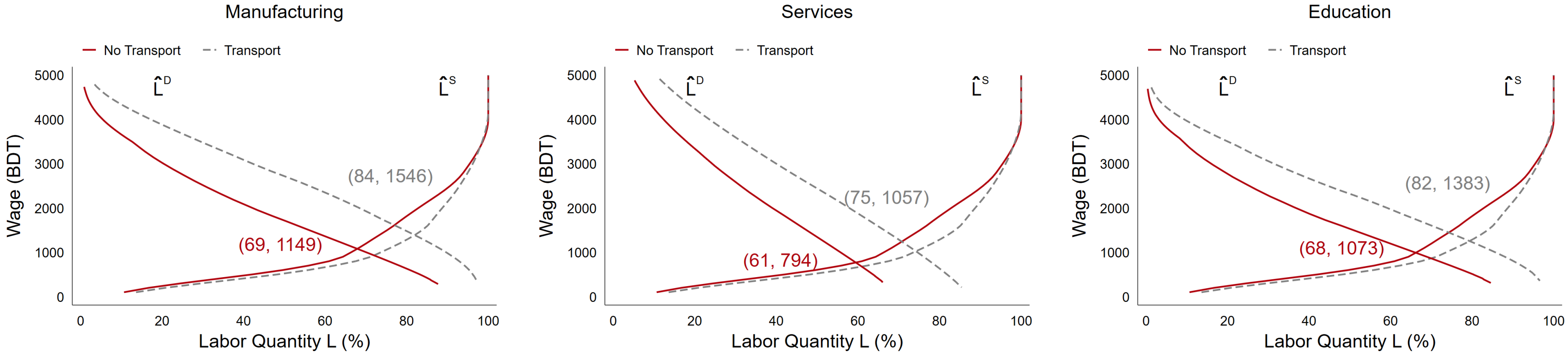
Notes: The graph shows the estimated coefficients and 95% confidence intervals of the preference parameters for a series of specifications.

Figure C.11: Equilibria in the Male and Female Labor Markets using the Preferred Piece Rate

(C.11.1) Market for Male Workers



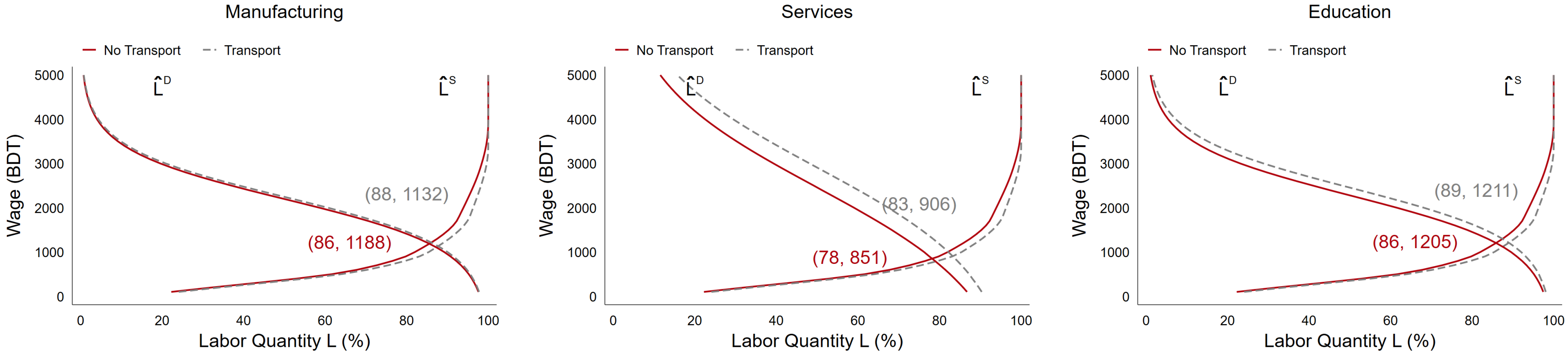
(C.11.2) Market for Female Workers



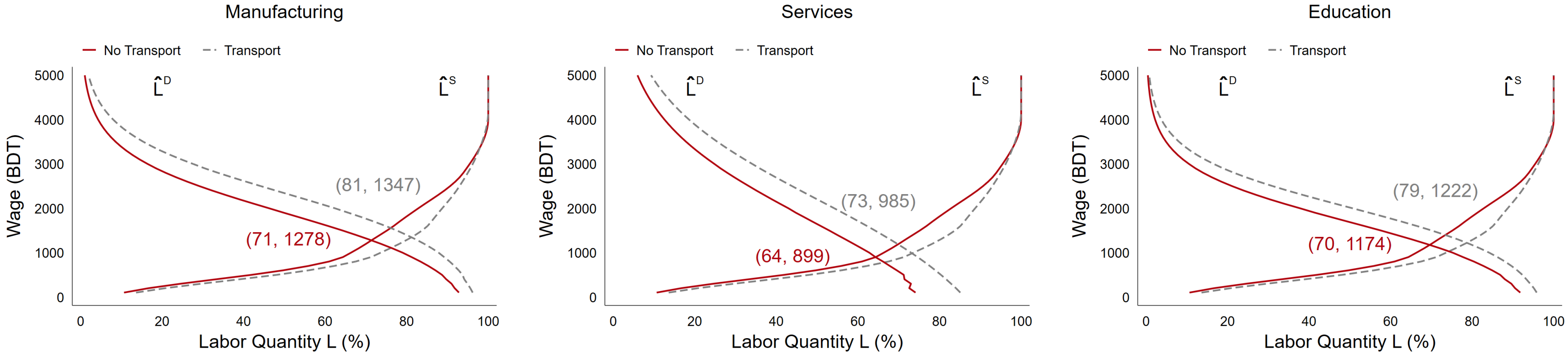
Notes: The graph shows the share of male and female workers demanded from equation 27 and the share of male and female workers supplied from equation 7 at each wage on a grid from 0 to 5,000 with and without transport by industry. We use predicted productivity and cost beliefs from the *Beliefs-Elicitation* employers (see section 6.1.3) and calculate profits using a piece rate of BDT 62 (USD 0.6). Numbers in parentheses in the graph give (L_g^*, w_g^*). Numbers in gray on the right-top are the equilibrium with transport and numbers in red on the left-bottom are the equilibrium without transport.

Figure C.12: Equilibria in the Male and Female Labor Markets using the Experimental Payoffs

(C.12.1) Market for Male Workers



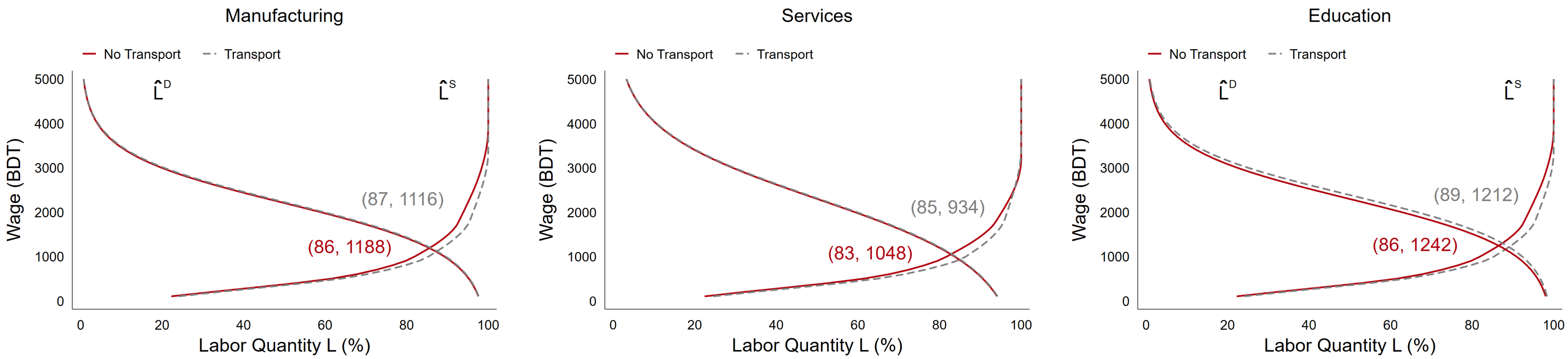
(C.12.2) Market for Female Workers



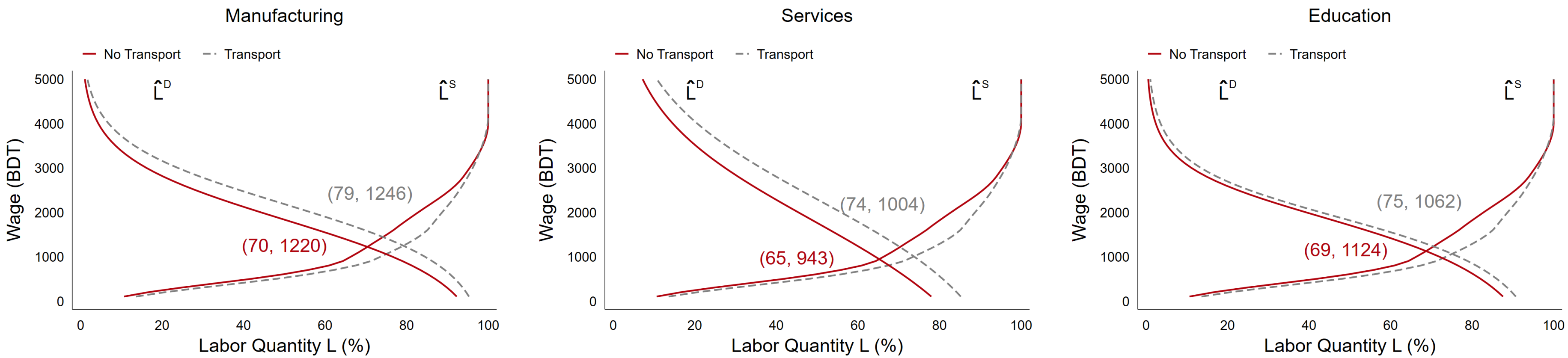
Notes: The graph shows the share of male and female workers demanded from equation 27 and the share of male and female workers supplied from equation 7 at each wage on a grid from 0 to 5,000 with and without transport by industry. We use predicted productivity and cost beliefs from the *Beliefs-Elicitation* employers (see section 6.1.3) and calculate profits using a base payment of BDT 2,000 (USD 20) and a piece rate of BDT 5 (USD 0.05). Numbers in parentheses in the graph give (L_g^*, w_g^*). Numbers in gray on the right-top are the equilibrium with transport and numbers in red on the left-bottom are the equilibrium without transport.

Figure C.13: Equilibria in the Male and Female Labor Markets, Holding Selection and Productivity Constant Across Wages and Transport Conditions

(C.13.1) Market for Male Workers



(C.13.2) Market for Female Workers



Notes: The graph shows the share of male and female workers demanded from equation 27 and the share of male and female workers supplied from equation 7 at each wage on a grid from 0 to 5,000 with and without transport by industry. We use predicted productivity and cost beliefs from the *Hiring* employers (see section 6.1.3) and calculate profits using a piece rate of BDT 62 (USD 0.6). Numbers in parentheses in the graph give (L_g^*, w_g^*). Numbers in gray on the right-top are the equilibrium with transport and numbers in red on the left-bottom are the equilibrium without transport.

C.2 Tables

Table C.1: Employer Characteristics, by Industry

	Manufacturing		Services		Education	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Female (%)	4.5	20.8	1.3	11.5	13.1	33.9
Age	32.4	7.8	32.1	7.8	30.0	7.7
Married (%)	72.9	44.6	61.6	48.8	41.9	49.5
Children (%)	58.7	49.4	49.0	50.2	28.8	45.4
Bachelor's (%)	12.3	33.0	31.5	46.6	81.2	39.2
Male Employees	10.9	37.4	3.2	4.0	12.3	16.9
Female Employees	11.3	70.6	0.2	0.9	6.3	9.5
Hiring Decisions Last 3 Years	52.8	402.7	10.2	25.4	17.7	36.9

Notes: The table shows the means and standard deviations of characteristics of employers by industry in the analysis sample of the hiring experiment. *Children* is an indicator that is 1 if the applicant has children.

Table C.2: Employer Characteristics in the Hiring Experiment, By Transport Information and Subsidy Assignment

	No Transport (NT)		**Male Subsidy (MS)**		**Female Subsidy (FS)**		**Employer Subsidy (ES)**		**NT+MS**		**NT+FS**		**NT+ES**		**Control**
N	101		36		47		60		39		47		36		94
	Mean (SD)	β_{NT} (p-val)	Mean (SD)	β_{MS} (p-val)	Mean (SD)	β_{FS} (p-val)	Mean (SD)	β_{ES} (p-val)	Mean (SD)	β_{NT+MS} (p-val)	Mean (SD)	β_{NT+FS} (p-val)	Mean (SD)	β_{NT+ES} (p-val)	Mean (SD)
Manufacturing (%)	34.65	3.80	36.11	5.26	36.17	5.32	33.33	2.48	41.03	1.11	27.66	-12.31	27.78	-9.36	30.85
	(47.82)	(0.57)	(48.71)	(0.58)	(48.57)	(0.53)	(47.54)	(0.75)	(49.83)	(0.93)	(45.22)	(0.30)	(45.43)	(0.43)	(46.44)
Retail & Services (%)	37.62	0.39	33.33	-3.90	25.53	-11.70	30.00	-7.23	35.90	2.17	23.40	-2.52	25.00	-5.39	37.23
	(48.69)	(0.96)	(47.81)	(0.68)	(44.08)	(0.15)	(46.21)	(0.35)	(48.60)	(0.87)	(42.80)	(0.82)	(43.92)	(0.65)	(48.60)
Education (%)	27.72	-4.19	30.56	-1.36	38.30	6.38	36.67	4.75	23.08	-3.29	48.94	14.83	47.22	14.75	31.91
	(44.99)	(0.53)	(46.72)	(0.88)	(49.14)	(0.46)	(48.60)	(0.55)	(42.68)	(0.79)	(50.53)	(0.22)	(50.63)	(0.23)	(46.86)
Age	31.51	0.36	31.25	0.09	30.94	-0.22	32.27	1.11	32.62	1.01	29.23	-2.06	33.31	0.68	31.16
	(7.28)	(0.74)	(7.00)	(0.95)	(7.81)	(0.87)	(8.98)	(0.43)	(7.54)	(0.61)	(7.22)	(0.28)	(9.14)	(0.76)	(7.80)
Bachelor's (%)	41.58	-3.58	44.44	-0.72	42.55	-2.61	38.33	-6.83	32.43	-8.43	40.43	1.45	52.78	18.02	45.16
	(49.53)	(0.62)	(50.40)	(0.94)	(49.98)	(0.77)	(49.03)	(0.41)	(47.46)	(0.53)	(49.61)	(0.91)	(50.63)	(0.16)	(50.04)
Married (%)	66.34	15.27	55.56	4.49	57.45	6.38	58.33	7.27	71.79	0.97	48.94	-23.78	58.33	-15.27	51.06
	(47.49)	(0.03)	(50.40)	(0.65)	(49.98)	(0.48)	(49.72)	(0.38)	(45.59)	(0.94)	(50.53)	(0.06)	(50.00)	(0.23)	(50.26)
Children (%)	49.50	11.21	41.67	3.37	44.68	6.38	50.00	11.70	61.54	8.66	34.04	-21.85	44.44	-16.76	38.30
	(50.25)	(0.12)	(50.00)	(0.73)	(50.25)	(0.47)	(50.42)	(0.16)	(49.29)	(0.52)	(47.90)	(0.08)	(50.40)	(0.19)	(48.87)
Daughters	0.36	0.05	0.36	0.05	0.34	0.03	0.48	0.17	0.44	0.03	0.34	-0.05	0.39	-0.14	0.31
	(0.61)	(0.59)	(0.64)	(0.67)	(0.64)	(0.78)	(0.77)	(0.14)	(0.72)	(0.88)	(0.67)	(0.77)	(0.69)	(0.42)	(0.64)
Female Employees	13.99	11.34	2.69	0.05	2.51	-0.14	4.68	2.03	6.00	-8.04	6.40	-7.45	2.58	-13.44	2.65
	(86.55)	(0.19)	(4.90)	(0.97)	(6.27)	(0.91)	(11.26)	(0.22)	(15.20)	(0.38)	(12.36)	(0.40)	(5.65)	(0.13)	(7.59)
Hiring Decisions Last 6 Months	66.75	55.78	11.19	0.23	12.04	1.07	14.10	3.13	29.41	-37.57	17.57	-50.25	25.83	-44.05	10.97
	(496.98)	(0.26)	(16.59)	(0.94)	(19.00)	(0.72)	(19.55)	(0.26)	(85.42)	(0.47)	(27.72)	(0.31)	(66.02)	(0.39)	(11.20)
All Understanding Questions Correct (%)	96.19	0.27	94.74	-1.18	95.92	-0.00	98.36	2.44	86.67	-8.34	87.04	-9.15	92.31	-6.33	95.92
	(19.23)	(0.92)	(22.63)	(0.78)	(19.99)	(1.00)	(12.80)	(0.35)	(34.38)	(0.22)	(33.90)	(0.13)	(27.00)	(0.24)	(19.89)
Made Hiring Choices b/c of Taste (%)	4.95	2.82	5.56	3.43	0.00	-2.13	0.00	-2.13	7.69	-0.69	2.13	-0.70	0.00	-2.82	2.13
	(21.80)	(0.29)	(23.23)	(0.41)	(0.00)	(0.16)	(0.00)	(0.16)	(27.00)	(0.91)	(14.59)	(0.84)	(0.00)	(0.29)	(14.51)
Made Hiring Choices b/c of Productivity (%)	100.00	2.13	97.22	-0.65	100.00	2.13	100.00	2.13	100.00	0.65	100.00	-2.13	100.00	-2.13	97.87
	(0.00)	(0.16)	(16.67)	(0.84)	(0.00)	(0.16)	(0.00)	(0.16)	(0.00)	(0.84)	(0.00)	(0.16)	(0.00)	(0.16)	(14.51)
P-value from joint significance test		0.47		0.99		0.72		0.29		0.96		0.47		0.19	
Made Hiring Choices b/c of Applicant Welfare (%)	82.39	25.72	80.91	24.25	65.63	8.96	73.43	16.76	67.19	-39.45	74.36	-16.99	58.32	-40.83	56.67
	(38.10)	(0.00)	(39.33)	(0.00)	(47.52)	(0.30)	(44.19)	(0.03)	(46.98)	(0.00)	(43.69)	(0.14)	(49.34)	(0.00)	(49.57)

Notes: The table shows characteristics by treatment arm of all employers in the analysis sample of the hiring experiment (except for "All Understanding Questions Correct (%)", for which we include all employers). "Made Hiring Choices b/c of Taste" is an indicator that is 1 for employers who reported that women belong at home. "Made Hiring Choices b/c of Productivity" is an indicator that is 1 for employers who report that they based their hiring choices based on absenteeism, performance, firm reputation, experience, education, or because women are hard to manage. "Made Hiring Choices b/c of Applicant Welfare" is an indicator that is 1 for employers who report that they based their hiring choices based on the applicants' safety, health, or marital status, or because they stated it would be inappropriate for women to work at night or that men would need money more than women. We show means and standard deviations within treatment arms as well as coefficients and p-values on the treatment indicators in OLS regressions with modified Huber-White robust SEs. P-values from joint significance test do not include the variable "Education (%)", which is perfectly collinear with "Manufacturing (%)" and "Retail & Services (%)".

Table C.3: Applicant Characteristics and Beliefs about Applicants in the Hiring Experiment, By Transport Information and Subsidy Assignment

	No Transport (NT)		**Male Subsidy (MS)**		**Female Subsidy (FS)**		**Employer Subsidy (ES)**		**NT+MS**		**NT+FS**		**NT+ES**		**Control**
	Mean (SD)	β_{NT} (p-val)	Mean (SD)	β_{MS} (p-val)	Mean (SD)	β_{FS} (p-val)	Mean (SD)	β_{ES} (p-val)	Mean (SD)	β_{NT+MS} (p-val)	Mean (SD)	β_{NT+FS} (p-val)	Mean (SD)	β_{NT+ES} (p-val)	Mean (SD)
Male Applicants: N	994		350		465		589		385		468		357		929
Age	24.43	0.25	24.44	0.26	24.45	0.26	25.02	0.84	24.99	0.31	24.52	-0.17	24.05	-1.22	24.19
	(5.47)	(0.32)	(5.63)	(0.38)	(5.67)	(0.35)	(6.21)	(0.01)	(6.24)	(0.48)	(5.83)	(0.69)	(5.22)	(0.01)	(5.22)
Education (Yrs)	39.33	2.68	36.78	0.13	36.74	0.09	40.55	3.89	39.95	0.49	35.71	-3.71	36.83	-6.40	36.65
	(48.87)	(0.21)	(48.29)	(0.96)	(48.26)	(0.97)	(49.14)	(0.12)	(49.04)	(0.90)	(47.97)	(0.29)	(48.30)	(0.09)	(48.21)
$\leq$ 3 Years Work Experience (%)	81.99	-0.03	77.71	-4.31	79.78	-2.24	81.66	-0.36	80.78	3.10	80.98	1.23	82.35	0.72	82.02
	(38.44)	(0.98)	(41.68)	(0.06)	(40.20)	(0.26)	(38.73)	(0.85)	(39.45)	(0.31)	(39.29)	(0.68)	(38.18)	(0.80)	(38.42)
Excel Screening Score (%)	23.45	0.77	23.17	0.49	22.76	0.08	23.47	0.79	23.19	-0.75	22.18	-1.35	23.05	-1.19	22.68
	(13.30)	(0.20)	(12.71)	(0.57)	(12.20)	(0.91)	(13.56)	(0.22)	(12.11)	(0.51)	(12.21)	(0.17)	(13.29)	(0.27)	(12.61)
Married (%)	18.41	0.33	18.86	0.77	18.92	0.84	20.54	2.46	20.52	1.34	18.59	-0.66	17.37	-3.50	18.08
	(38.78)	(0.84)	(39.17)	(0.71)	(39.21)	(0.64)	(40.44)	(0.23)	(40.44)	(0.65)	(38.94)	(0.82)	(37.94)	(0.22)	(38.51)
Children (%)	10.26	0.25	11.14	1.13	11.18	1.17	12.39	2.38	13.77	2.37	11.11	-0.32	9.24	-3.40	10.01
	(30.36)	(0.85)	(31.51)	(0.54)	(31.55)	(0.43)	(32.98)	(0.15)	(34.50)	(0.34)	(31.46)	(0.89)	(29.00)	(0.14)	(30.03)
P-value from joint significance test		0.60		0.72		0.96		0.03		0.87		0.59		0.04	
Productivity (P(Show-up) $\times$ E[Tasks|Show-up])	39.81	1.14	39.75	1.09	34.86	-3.81	38.05	-0.62	47.78	6.88	40.99	4.99	35.05	-4.14	38.67
	(21.24)	(0.65)	(21.04)	(0.76)	(18.47)	(0.20)	(21.32)	(0.84)	(22.28)	(0.17)	(22.19)	(0.26)	(19.66)	(0.35)	(20.17)
Predicted Revenue (BDT)	698.57	3.78	701.14	6.35	674.57	-20.22	690.32	-4.47	738.36	33.43	704.97	26.62	674.71	-19.40	694.80
	(106.61)	(0.77)	(106.36)	(0.73)	(92.82)	(0.18)	(107.07)	(0.77)	(112.02)	(0.19)	(110.95)	(0.23)	(97.36)	(0.38)	(100.85)
Actual Revenue (BDT)	585.27	0.57	585.45	0.75	586.02	1.32	583.98	-0.72	587.80	1.78	586.07	-0.52	583.99	-0.56	584.70
	(28.53)	(0.79)	(29.46)	(0.79)	(27.81)	(0.61)	(29.50)	(0.77)	(29.35)	(0.65)	(27.88)	(0.88)	(29.20)	(0.88)	(29.18)
P-value from joint significance test		0.43		0.19		0.70		0.44		0.52		0.17		0.67	
Perceived Costs (0–10)	2.49	1.62	1.08	0.22	0.63	-0.23	0.72	-0.14	1.90	-0.81	2.18	-0.07	1.81	-0.54	0.87
	(2.17)	(0.00)	(1.10)	(0.29)	(1.25)	(0.22)	(1.21)	(0.43)	(1.80)	(0.04)	(1.86)	(0.85)	(2.04)	(0.21)	(1.20)
Perceived Costs (BDT)	1420.89	936.88	608.93	124.92	364.12	-119.89	413.81	-70.20	1068.33	-477.47	1239.36	-61.64	1054.46	-296.23	484.01
	(1235.65)	(0.00)	(625.92)	(0.29)	(712.16)	(0.27)	(691.06)	(0.49)	(1028.17)	(0.04)	(1058.75)	(0.78)	(1161.15)	(0.22)	(682.56)
Female Applicants: N	993		352		466		589		386		468		358		931
Age	23.65	0.10	23.44	-0.11	23.70	0.14	23.51	-0.05	23.53	-0.01	23.54	-0.26	24.03	0.43	23.55
	(5.89)	(0.75)	(5.88)	(0.76)	(6.06)	(0.69)	(5.82)	(0.88)	(5.70)	(0.99)	(5.72)	(0.61)	(6.52)	(0.40)	(6.12)
Education (Yrs)	37.76	1.30	35.90	-0.56	34.19	-2.27	36.69	0.23	35.77	-1.43	33.98	-1.52	38.20	0.21	36.46
	(48.50)	(0.57)	(48.04)	(0.84)	(47.49)	(0.37)	(48.24)	(0.93)	(48.00)	(0.72)	(47.41)	(0.69)	(48.66)	(0.95)	(48.16)
$\leq$ 3 Years Work Experience (%)	89.12	-0.03	89.77	0.62	87.55	-1.60	89.64	0.49	86.53	-3.22	89.32	1.79	86.87	-2.74	89.15
	(31.15)	(0.98)	(30.34)	(0.70)	(33.05)	(0.34)	(30.50)	(0.75)	(34.19)	(0.16)	(30.92)	(0.42)	(33.82)	(0.29)	(31.12)
Excel Screening Score (%)	24.78	0.71	24.56	0.48	24.62	0.55	24.26	0.19	25.41	0.15	24.41	-0.92	24.58	-0.39	24.08
	(13.55)	(0.30)	(13.62)	(0.61)	(13.40)	(0.52)	(13.53)	(0.81)	(13.79)	(0.91)	(13.31)	(0.43)	(14.04)	(0.75)	(13.07)
Married (%)	22.05	-0.39	21.59	-0.86	22.53	0.08	22.24	-0.21	23.32	2.12	22.01	-0.13	22.07	0.22	22.45
	(41.48)	(0.84)	(41.20)	(0.72)	(41.82)	(0.97)	(41.62)	(0.92)	(42.34)	(0.53)	(41.47)	(0.97)	(41.53)	(0.95)	(41.75)
Children (%)	11.28	0.32	10.51	-0.44	12.45	1.49	12.56	1.61	11.40	0.56	11.11	-1.66	12.29	-0.60	10.96
	(31.65)	(0.83)	(30.71)	(0.82)	(33.05)	(0.46)	(33.17)	(0.37)	(31.82)	(0.84)	(31.46)	(0.54)	(32.88)	(0.84)	(31.25)
P-value from joint significance test		0.87		0.99		0.51		0.43		0.92		0.57		0.71	
Productivity (P(Show-up) $\times$ E[Tasks|Show-up])	31.72	0.62	28.87	-2.23	25.37	-5.73	30.83	-0.27	36.60	7.12	32.23	6.25	27.35	-4.10	31.10
	(19.50)	(0.80)	(17.96)	(0.45)	(17.63)	(0.04)	(20.83)	(0.93)	(22.98)	(0.13)	(21.55)	(0.14)	(19.81)	(0.35)	(21.20)
Predicted Revenue (BDT)	657.81	2.01	644.95	-10.84	626.83	-28.97	654.51	-1.28	683.02	36.06	661.17	32.33	635.79	-20.74	655.80
	(97.07)	(0.87)	(90.27)	(0.47)	(88.17)	(0.04)	(104.53)	(0.93)	(114.88)	(0.13)	(107.75)	(0.12)	(99.39)	(0.35)	(106.19)
Actual Revenue (BDT)	588.25	5.43	583.17	0.35	587.39	4.57	592.52	9.70	588.39	-0.21	586.05	-6.77	590.76	-7.19	582.82
	(28.26)	(0.10)	(30.32)	(0.94)	(30.64)	(0.29)	(26.52)	(0.01)	(28.23)	(0.97)	(29.21)	(0.27)	(27.65)	(0.17)	(29.42)
P-value from joint significance test		0.72		0.05		0.62		0.69		0.13		0.28		0.84	
Perceived Costs (0–10)	6.30	3.05	4.43	1.18	3.00	-0.25	3.07	-0.19	6.01	-1.46	5.84	-0.21	5.17	-0.95	3.25
	(2.50)	(0.00)	(2.02)	(0.00)	(2.20)	(0.48)	(2.18)	(0.59)	(2.17)	(0.01)	(2.31)	(0.70)	(2.92)	(0.13)	(2.20)
Perceived Costs (BDT)	3576.57	1736.24	2525.49	685.16	1702.31	-138.03	1735.97	-104.36	3411.99	-849.74	3313.10	-125.45	2917.11	-555.10	1840.34
	(1428.11)	(0.00)	(1150.13)	(0.00)	(1246.57)	(0.50)	(1242.07)	(0.60)	(1229.81)	(0.01)	(1310.32)	(0.68)	(1662.10)	(0.12)	(1249.41)

Notes: The table shows characteristics by treatment arm of all applicants in the hiring experiment as well as employers' beliefs about them. We show means and standard deviations within treatment arms as well as coefficients and p-values on the treatment indicators in OLS regressions with modified Huber–White robust SEs.

Table C.4: Productivity and Costs Predictions from *Hiring* and *Prediction-Only* Employers

	Employer Type		
	Hiring		**Prediction**
	Mean (SD)	$\beta_{Prediction}$ (p-val)	Mean (SD)
Male Applicants: N	1,414		320
Productivity ($P(\text{Show-up}) \times E[\text{Tasks}\|\text{Show-up}]$)	41.54	-3.74	37.80
	(22.09)	(0.12)	(21.27)
Perceived Costs (0–10)	2.27	0.17	2.44
	(2.06)	(0.56)	(2.22)
Female Applicants: N	1,412		320
Productivity ($P(\text{Show-up}) \times E[\text{Tasks}\|\text{Show-up}]$)	32.27	-2.92	29.35
	(21.92)	(0.22)	(20.00)
Perceived Costs (0–10)	6.06	-0.41	5.64
	(2.44)	(0.18)	(2.27)

Notes: The table shows predictions for a subset of applicants for which both *Hiring* and *Prediction-Only* employers made predictions. We show means, standard deviations, and results from OLS regressions with modified Huber–White SEs. We show coefficients and p-values on an indicator that is 1 for Prediction-Only employers. Including all data once prediction surveys started (as Prediction-Only surveys were only conducted during the second half of data collection).

Table C.5: Hired by Transport Information and Subsidy Assignment, Robustness Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
No transport (NT)	-9.865***	-9.756***	-9.865***	-9.310***	-9.513***	-10.081***	-11.607***	-9.919***	-9.865***	-0.625***	-34.902***
	(2.492)	(2.450)	(2.494)	(2.468)	(2.450)	(2.476)	(3.543)	(2.597)	(2.637)	(0.150)	(6.021)
Male subsidy (MS)	-7.257**	-6.941**	-7.257**	-6.310*	-6.847**	-6.864**	-9.094**	-7.098**	-7.257**	-0.458**	
	(3.259)	(3.271)	(3.261)	(3.269)	(3.061)	(3.226)	(4.145)	(3.253)	(3.490)	(0.191)	
Female subsidy (FS)	7.198***	4.800*	7.198***	4.804*	7.677***	7.708***	8.298**	6.784**	7.198**	0.432***	
	(2.769)	(2.676)	(2.771)	(2.710)	(2.742)	(2.810)	(3.677)	(2.860)	(2.953)	(0.159)	
Employer subsidy (ES)	23.080***	22.922***	23.080***	23.040***	22.944***	23.247***	23.136***	22.493***	23.080***	1.392***	
	(3.114)	(3.071)	(3.116)	(3.092)	(3.075)	(3.131)	(4.334)	(3.213)	(3.289)	(0.190)	
NT*MS	1.192	-0.607	1.192	-0.777	1.275	1.218	3.184	1.780	1.192	0.078	
	(4.394)	(4.321)	(4.398)	(4.366)	(4.296)	(4.377)	(5.992)	(4.567)	(4.696)	(0.268)	
NT*FS	-4.697	-3.585	-4.697	-4.195	-6.639*	-4.720	-7.297	-4.631	-4.697	-0.254	
	(4.098)	(4.043)	(4.101)	(4.039)	(3.926)	(4.119)	(5.776)	(4.162)	(4.301)	(0.239)	
NT*ES	0.443	-0.601	0.443	-1.044	0.264	1.285	0.760	0.988	0.443	0.023	
	(5.324)	(5.247)	(5.328)	(5.286)	(5.104)	(5.357)	(7.802)	(5.427)	(5.538)	(0.307)	
Applicant: Excel score		1.330***		1.311***							
		(0.060)		(0.061)							
Applicant: Education		2.282***		1.862***							
		(0.311)		(0.305)							
Applicant: $\leq$ 3 yrs work experience		-10.630***									
		(2.332)									
Applicant: Married		-5.681***									
		(2.064)									
Applicant: Has children		-1.702									
		(2.804)									
Control Mean	45.328	45.279	45.279	45.328	45.979	45.168	48.092	46.007	45.328	45.328	55.000
Observations	4543	4550	4550	4543	4826	4493	2573	4091	4543	4184	241
Main	✓										
No fixed effects		✓									
No controls			✓								
Post-Double-Selection				✓							
Understanding					✓						
Correct commute						✓					
Before first shift							✓				
No prediction applicants								✓			
Two-way clustering									✓		
Logit										✓	
Candidate 1 versus 2											✓

Notes: The table shows results from OLS regressions with Huber–White robust SEs clustered at the employer level (see notes to figure 3). Column (2) excludes applicant fixed effects, column (3) excludes all covariates, and column (4) uses covariates selected using the post-double selection (PSD) Lasso method of Belloni et al. (2014). Column (5) includes employers who answer understanding questions incorrectly, column (6) includes only employers who report that women in the *Transport* treatment will get home using provided transport and that women in the *No Transport* treatment will not get home using provided transport, and column (7) includes only employers surveyed before the first night shift. Column (8) excludes the applicants from the application experiment. column (9) clusters standard errors both at the employer and the applicant level, column (10) uses a Logit specification, and column (11) includes hiring decisions over candidate 1 versus 2 (not disaggregated by subsidies and using the covariates from column (2) as we do not have sufficient observations).

Table C.6: Hired by Transport Information and Subsidy Assignment, Extensive versus Intensive Margin Effects

	Hired Woman (%)	# Women
	(1)	(2)
No transport (NT)	-0.106*	-1.011*
	(0.064)	(0.525)
Male subsidy (MS)	-0.176**	-1.014
	(0.077)	(0.806)
Female subsidy (FS)	-0.163**	0.170
	(0.070)	(0.627)
Employer subsidy (ES)	0.066	0.426
	(0.080)	(0.607)
NT*MS	0.142	1.755*
	(0.107)	(0.953)
NT*FS	0.133	0.038
	(0.098)	(0.841)
NT*ES	0.087	0.616
	(0.120)	(1.254)
Control Mean	0.319	3.640
Observations	460	113

Notes: The table shows results from OLS regressions with Huber–White robust SEs, controlling for the mean characteristics of both applicants per employer and industry fixed effects. The unit of observation is the employer. Column (1) keeps all employers who correctly answer the understanding questions. The outcome is whether the employer hires at least one woman. Column (2) keeps all employers who answer the understanding questions correctly and hire at least one woman. The outcome is the number of women hired by the employer.

Table C.7: Applicant Characteristics in the Application Experiment, by Transport Information

	No Transport (NT)		**Control**
Male Applicants			
N	171		183
	Mean (SD)	β_{NT} (p-val)	Mean (SD)
Age	25.34	-1.07	26.49
	(7.26)	(0.36)	(8.56)
Education (Years)	14.43	-0.05	14.64
	(2.36)	(0.89)	(2.29)
$\leq$ 3 Years Work Experience (%)	73.68	3.68	71.58
	(44.16)	(0.59)	(45.22)
Excel Screening Score (%)	24.65	0.44	25.08
	(11.65)	(0.80)	(11.38)
Married (%)	23.98	-2.12	27.32
	(42.82)	(0.74)	(44.68)
Children (%)	18.71	-0.58	18.03
	(39.12)	(0.92)	(38.55)
All Understanding Questions Correct (%)	89.53	-4.15	91.50
	(30.70)	(0.30)	(27.96)
P-value from joint significance test		0.80	
Reported Costs (0–10)	2.30	0.35	1.81
	(2.44)	(0.23)	(2.33)
Female Applicants			
N	175		169
	Mean (SD)	β_{NT} (p-val)	Mean (SD)
Age	23.01	0.76	23.05
	(6.37)	(0.49)	(6.64)
Education (Years)	13.70	-0.29	13.86
	(2.21)	(0.43)	(2.30)
$\leq$ 3 Years Work Experience (%)	86.29	-9.62	90.53
	(34.50)	(0.08)	(29.36)
Excel Screening Score (%)	26.31	0.06	26.42
	(12.01)	(0.97)	(12.27)
Married (%)	21.14	-6.38	27.22
	(40.95)	(0.37)	(44.64)
Children (%)	10.29	-8.92	17.16
	(30.46)	(0.13)	(37.82)
All Understanding Questions Correct (%)	93.58	6.43	88.02
	(24.57)	(0.10)	(32.56)
P-value from joint significance test		0.14	
Reported Costs (0–10)	5.89	0.82	4.88
	(2.97)	(0.03)	(3.05)

Notes: The table shows characteristics by treatment arm of all female and male workers in the application experiment. We show means and standard deviations within treatment arms as well as coefficients and p-values on the treatment indicators from regression 4 without applicant controls.

Table C.8: Reservation Wages in the Application Experiment by Transport Information, Robustness Analysis

	Male Workers							Female Workers						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
No transport (NT)	164.874*	-0.044	136.797*	215.348	177.072**	201.023**	174.136**	239.841*	-0.130*	246.949*	215.525	238.095*	221.388	162.023
	(92.092)	(0.047)	(75.948)	(145.723)	(88.047)	(89.544)	(85.580)	(141.490)	(0.069)	(128.997)	(173.132)	(137.016)	(136.059)	(135.064)
Control Mean	479.781	0.934	410.286	553.552	479.781	479.781	476.000	802.663	0.858	735.671	848.521	802.663	802.663	810.677
Observations	354	354	337	354	354	354	391	344	344	333	344	344	344	379
Main	✓							✓						
Applied		✓							✓					
Truncating			✓							✓				
Keep outliers				✓							✓			
No controls					✓							✓		
Post-Double-Selection						✓							✓	
Understanding							✓							✓

Notes: The table shows results from OLS regressions with Huber–White robust SEs (see equation 4 and notes to figure 5). We always control for assignment to the *High promotion* treatment and its interaction with *No transport*. We winsorize the data at the 95th percentile and control for the worker's education, marriage status (unmarried, married without children, or married with children), work experience, Excel screening score, and age in the main specification in columns (1) and (9). We use a reservation wage of $\leq$ BDT 1,500 (the wage in the hiring experiment) as an outcome in columns (2) and (10). We truncate the data at the 95th percentile in columns (3) and (11) and do not exclude outliers in columns (4) and (12). We exclude all covariates in columns (5) and (13) and include covariates selected using the post-double selection (PSD) Lasso method of Belloni et al. (2014) in columns (6) and (14). We include applicants with incorrect understanding questions in columns (7) and (15).

Table C.9: Control Functions

	Outcome: Π_{ik}				Outcome: $\mathcal{W}_{ik}$			
	Pooled	**Manufacturing** $j=1$	**Services** $j=2$	**Education** $j=3$	**Pooled**	**Manufacturing** $j=1$	**Services** $j=2$	**Education** $j=3$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.038***	-0.042***	-0.048***	-0.022	-1.372***	-1.411***	-1.328***	-1.374***
	(0.006)	(0.010)	(0.010)	(0.013)	(0.114)	(0.206)	(0.196)	(0.192)
No transport (NT)	0.004	0.054***	-0.013	-0.018	-0.936***	-1.413***	-0.814***	-0.641***
	(0.012)	(0.020)	(0.022)	(0.020)	(0.130)	(0.272)	(0.201)	(0.211)
Employer subsidy (ES)	-0.004	0.037*	-0.028	-0.016	0.104	0.010	0.136	0.171
	(0.014)	(0.022)	(0.025)	(0.023)	(0.101)	(0.201)	(0.110)	(0.193)
Male subsidy (MS)	0.007	0.010	-0.036	0.046	0.889***	0.721***	0.765***	1.146***
	(0.018)	(0.030)	(0.022)	(0.035)	(0.122)	(0.229)	(0.173)	(0.215)
Female subsidy (FS)	-0.017	-0.002	-0.035	-0.011	0.183*	0.156	0.084	0.235
	(0.014)	(0.019)	(0.029)	(0.026)	(0.109)	(0.191)	(0.159)	(0.207)
NT*ES	-0.014	-0.083***	0.020	0.005	0.353	0.762*	0.748***	-0.345
	(0.021)	(0.031)	(0.049)	(0.038)	(0.231)	(0.429)	(0.283)	(0.405)
NT*MS	0.031	-0.005	0.096**	-0.001	0.472**	1.195***	0.299	0.113
	(0.025)	(0.046)	(0.039)	(0.041)	(0.230)	(0.390)	(0.390)	(0.381)
NT*FS	0.026	-0.007	0.026	0.037	0.075	0.291	0.458	-0.304
	(0.021)	(0.034)	(0.039)	(0.035)	(0.214)	(0.382)	(0.311)	(0.413)
NT*Female	0.001	-0.007	0.006	-0.003	-0.798***	-0.321	-0.945***	-1.031***
	(0.011)	(0.020)	(0.019)	(0.018)	(0.166)	(0.295)	(0.281)	(0.282)
ES*Female	1.008***	0.986***	1.023***	1.007***	0.039	-0.276	0.506*	-0.068
	(0.011)	(0.018)	(0.018)	(0.021)	(0.174)	(0.323)	(0.277)	(0.266)
MS*Female	-0.015	-0.008	0.030	-0.069**	-1.532***	-1.630***	-1.256***	-1.720***
	(0.018)	(0.030)	(0.031)	(0.031)	(0.244)	(0.382)	(0.388)	(0.479)
FS*Female	-0.005	0.002	-0.003	-0.026	1.032***	0.592*	1.549***	1.067***
	(0.012)	(0.019)	(0.024)	(0.022)	(0.194)	(0.327)	(0.292)	(0.344)
NT*ES*Female	-0.009	0.016	-0.003	-0.016	0.232	0.183	-0.059	0.399
	(0.019)	(0.034)	(0.028)	(0.031)	(0.279)	(0.457)	(0.536)	(0.508)
NT*MS*Female	-0.005	0.028	-0.052	0.025	0.331	0.349	0.361	0.321
	(0.025)	(0.039)	(0.046)	(0.041)	(0.338)	(0.516)	(0.522)	(0.658)
NT*FS*Female	-0.004	-0.003	0.010	0.003	0.047	-0.107	-0.231	0.445
	(0.018)	(0.029)	(0.039)	(0.029)	(0.266)	(0.448)	(0.451)	(0.435)
Male Mean (NT+NS)	0.693	0.664	0.713	0.700	1.009	0.980	1.113	0.913
F-Stat	834.050	426.464	499.008	386.081	62.692	34.220	25.065	25.536
Observations	1826	624	592	610	1826	624	592	610

Notes: The table shows results from OLS regressions with Huber–White robust SEs clustered at the employer level. Controlling for all characteristics shown to the employer (initial Excel score, education, work experience, marriage status) as well as enumerator and employer industry $\times$ pair order (1–12) fixed effects.

Table C.10: Second-Stage Regression with fitted residuals, Outcome: Hired

	Pooled	**Manufacturing** $j = 1$	**Services** $j = 2$	**Education** $j = 3$
	(1)	(2)	(3)	(4)
Π (BDT ’000)	1.492***	1.932***	1.117***	1.637***
	(0.209)	(0.367)	(0.355)	(0.422)
Female	0.056	-0.122	-0.178	0.446
	(0.179)	(0.393)	(0.332)	(0.303)
$\mathcal{W}_m$ (BDT ’000)	0.308***	0.389	0.224	0.284
	(0.112)	(0.266)	(0.219)	(0.176)
$\mathcal{W}_f$ (BDT ’000)	0.383***	0.418	0.206	0.551***
	(0.095)	(0.259)	(0.147)	(0.133)
$\widehat{\varepsilon^{\Pi}}$ (BDT ’000)	0.963	0.570	0.185	2.083
	(0.945)	(2.009)	(1.568)	(1.589)
$\widehat{\varepsilon^{\mathcal{W}}}$ (BDT ’000)	-0.177	-0.183	0.103	-0.396**
	(0.110)	(0.278)	(0.183)	(0.178)
Observations	1826	624	592	610

Notes: The table shows results from Logit with Huber–White robust SEs clustered at the employer level. Controlling for all characteristics shown to the employer (initial Excel score, education, work experience, marriage status) as well as enumerator and employer industry × pair order (1–12) fixed effects.

Table C.11: Counterfactuals: Benchmarking the Importance of Paternalistic Discrimination

	Status Quo	$\alpha_m \mathcal{W}_m^E = \alpha_f \mathcal{W}_f^E$	$\mathcal{W}_m^E = \mathcal{W}_f^E$	$\alpha_m = \alpha_f$	$d = 0$	$\Pi_m^E = \Pi_f^E$	$L_m^S = L_f^S$	$\mathcal{W}_g^E = \mathcal{W}_g^{E:A}$	$\mathcal{W}_g^E = \mathcal{W}_g^A$
L_m^* (%)	85.00	85.00	85.00	85.00	85.00	85.00	85.00	85.00	86.00
L_f^* (%)	67.00	71.00	71.00	69.00	68.00	71.00	73.00	68.00	73.00
$L_m^* - L_f^*$ (ppts)	18.00	14.00	14.00	16.00	17.00	14.00	12.00	17.00	13.00
w_m^* (BDT)	1152.00	1152.00	1152.00	1152.00	1152.00	1152.00	1152.00	1176.00	1219.00
w_f^* (BDT)	1017.00	1283.00	1275.00	1117.00	1095.00	1234.00	702.00	1083.00	1397.00
$w_m^* - w_f^*$ (BDT)	135.00	-131.00	-123.00	35.00	57.00	-82.00	450.00	93.00	-178.00
$\mathcal{W}_m^E$ (’000 BDT)	-129.39	-129.39	-129.39	-129.39	-129.39	-129.39	-129.39	-119.30	-102.39
$\mathcal{W}_m^A$ (’000 BDT)	219.35	219.35	219.35	219.35	219.35	219.35	219.35	229.44	250.45
$\mathcal{W}_f^E$ (’000 BDT)	-834.18	-790.03	-792.85	-824.92	-820.37	-807.71	-1039.02	-824.41	-771.09
$\mathcal{W}_f^A$ (’000 BDT)	107.28	203.42	200.60	144.30	134.81	186.75	75.82	130.77	250.34

Notes: The table shows the results from the industry counterfactuals. We use both employers’ and applicants’ beliefs about the job costs and productivity in our experiment. We conduct the following counterfactual exercises: 1) eliminating paternalistic discrimination, either by equalizing male and female other-regarding utility, $\alpha_m \mathcal{W}_m^E = \alpha_f \mathcal{W}_f^E$, by equalizing male and female perceived welfare, $\mathcal{W}_m^E = \mathcal{W}_f^E$, or equalizing the welfare weights, $\alpha_m = \alpha_f$, 2) eliminating taste-based discrimination by setting $d = 0$, 3) eliminating statistical discrimination by equalizing male and female perceived profits, $\Pi_m^E = \Pi_f^E$, or 4) eliminating differences in labor supply by equalizing male and female labor supply, $L_m^S = L_f^S$. We present effects on the following outcomes: 1) male and female employment as well as the the gender employment gap, $L_m^*, L_f^*, L_m^* - L_f^*$ (in percentage points), 2) male and female wages as well as the gender wage gap, $w_m^*, w_f^*, w_m^* - w_f^*$ (in BDT), 3) total male welfare as perceived by employers, $\mathcal{W}_m^E$ (in ’000 BDT), and applicants, $\mathcal{W}_m^A$ (in ’000 BDT), 4) total female welfare as perceived by employers, $\mathcal{W}_f^E$ (in ’000 BDT) and applicants, $\mathcal{W}_f^A$ (in ’000 BDT).

Table C.12: Counterfactuals: Benchmarking the Importance of Paternalistic Discrimination Across Industries

	Status Quo	$\alpha_m \mathcal{W}_m^E = \alpha_f \mathcal{W}_f^E$	$\mathcal{W}_m^E = \mathcal{W}_f^E$	$\alpha_m = \alpha_f$	$d = 0$	$\Pi_m^E = \Pi_f^E$	$L_m^S = L_f^S$	$\mathcal{W}_g^E = \mathcal{W}_g^{E:A}$	$\mathcal{W}_g^E = \mathcal{W}_g^A$
Manufacturing									
L_m^* (%)	86.00	86.00	86.00	86.00	86.00	86.00	86.00	87.00	87.00
L_f^* (%)	69.00	74.00	74.00	73.00	69.00	73.00	77.00	76.00	70.00
$L_m^* - L_f^*$ (ppts)	17.00	12.00	12.00	13.00	17.00	13.00	9.00	11.00	17.00
w_m^* (BDT)	1241.00	1241.00	1241.00	1241.00	1241.00	1241.00	1241.00	1249.00	1244.00
w_f^* (BDT)	1149.00	1408.00	1417.00	1386.00	1166.00	1368.00	817.00	1533.00	1189.00
$w_m^* - w_f^*$ (BDT)	92.00	-167.00	-176.00	-145.00	75.00	-127.00	424.00	-284.00	55.00
$\mathcal{W}_m^E$ ('000 BDT)	-41.27	-41.27	-41.27	-41.27	-41.27	-41.27	-41.27	-38.31	-40.46
$\mathcal{W}_m^A$ ('000 BDT)	259.81	259.81	259.81	259.81	259.81	259.81	259.81	266.28	264.13
$\mathcal{W}_f^E$ ('000 BDT)	-738.84	-697.19	-693.89	-695.72	-733.03	-702.22	-956.96	-668.69	-735.69
$\mathcal{W}_f^A$ ('000 BDT)	155.23	257.80	261.10	246.37	158.27	239.86	111.32	267.75	168.53
Services									
L_m^* (%)	79.00	79.00	79.00	79.00	79.00	79.00	79.00	83.00	80.00
L_f^* (%)	61.00	68.00	69.00	59.00	62.00	66.00	64.00	71.00	63.00
$L_m^* - L_f^*$ (ppts)	18.00	11.00	10.00	20.00	17.00	13.00	15.00	12.00	17.00
w_m^* (BDT)	870.00	870.00	870.00	870.00	870.00	870.00	870.00	1030.00	911.00
w_f^* (BDT)	794.00	1111.00	1117.00	768.00	818.00	967.00	536.00	1278.00	862.00
$w_m^* - w_f^*$ (BDT)	76.00	-241.00	-247.00	102.00	52.00	-97.00	334.00	-248.00	49.00
$\mathcal{W}_m^E$ ('000 BDT)	-235.49	-235.49	-235.49	-235.49	-235.49	-235.49	-235.49	-175.72	-222.24
$\mathcal{W}_m^A$ ('000 BDT)	160.52	160.52	160.52	160.52	160.52	160.52	160.52	168.69	178.79
$\mathcal{W}_f^E$ ('000 BDT)	-843.92	-818.50	-828.49	-823.84	-850.39	-841.47	-971.72	-795.37	-850.38
$\mathcal{W}_f^A$ ('000 BDT)	81.24	140.19	144.30	70.98	89.94	89.35	24.13	201.66	102.61
Education									
L_m^* (%)	87.00	87.00	87.00	87.00	87.00	87.00	87.00	89.00	88.00
L_f^* (%)	68.00	72.00	72.00	68.00	70.00	72.00	75.00	74.00	69.00
$L_m^* - L_f^*$ (ppts)	19.00	15.00	15.00	19.00	17.00	15.00	12.00	15.00	19.00
w_m^* (BDT)	1298.00	1298.00	1298.00	1298.00	1298.00	1298.00	1298.00	1391.00	1332.00
w_f^* (BDT)	1073.00	1325.00	1322.00	1106.00	1216.00	1312.00	757.00	1444.00	1157.00
$w_m^* - w_f^*$ (BDT)	225.00	-27.00	-24.00	192.00	82.00	-14.00	541.00	-53.00	175.00
$\mathcal{W}_m^E$ ('000 BDT)	-120.57	-120.57	-120.57	-120.57	-120.57	-120.57	-120.57	-82.37	-107.14
$\mathcal{W}_m^A$ ('000 BDT)	285.71	285.71	285.71	285.71	285.71	285.71	285.71	333.25	303.81
$\mathcal{W}_f^E$ ('000 BDT)	-896.19	-858.56	-859.63	-885.08	-872.99	-863.19	-1121.86	-838.82	-880.67
$\mathcal{W}_f^A$ ('000 BDT)	127.40	221.25	220.18	138.51	177.88	216.62	86.15	270.99	155.19

Notes: The table shows the results from the industry counterfactuals. We use both employers' and applicants' beliefs about the job costs and productivity in our experiment. We conduct the following counterfactual exercises: 1) eliminating paternalistic discrimination, either by equalizing male and female other-regarding utility, $\alpha_m \mathcal{W}_m^E = \alpha_f \mathcal{W}_f^E$, by equalizing male and female perceived welfare, $\mathcal{W}_m^E = \mathcal{W}_f^E$, or equalizing the welfare weights, $\alpha_m = \alpha_f$, 2) eliminating taste-based discrimination by setting $d = 0$, 3) eliminating statistical discrimination by equalizing male and female perceived profits, $\Pi_m^E = \Pi_f^E$, or 4) eliminating differences in labor supply by equalizing male and female labor supply, $L_m^S = L_f^S$. We present effects on the following outcomes: 1) male and female employment as well as the the gender employment gap, $L_m^*, L_f^*, L_m^* - L_f^*$ (in percentage points), 2) male and female wages as well as the gender wage gap, $w_m^*, w_f^*, w_m^* - w_f^*$ (in BDT), 3) total male welfare as perceived by employers, $\mathcal{W}_m^E$ (in '000 BDT), and applicants, $\mathcal{W}_m^A$ (in '000 BDT), 4) total female welfare as perceived by employers, $\mathcal{W}_f^E$ (in '000 BDT) and applicants, $\mathcal{W}_f^A$ (in '000 BDT).

Table C.13: Counterfactuals: Estimating the Welfare Effects of Transport and Subsidy Interventions

	Status Quo	**Govt Trans**	**Subsidies**	**Empl Trans**
L_m^* (%)	85.00	85.00	85.00	85.00
L_f^* (%)	67.00	80.00	78.00	31.00
$L_m^* - L_f^*$ (ppts)	18.00	5.00	7.00	54.00
w_m^* (BDT)	1152.00	1152.00	1152.00	1152.00
w_f^* (BDT)	1017.00	1312.00	1680.00	379.00
$w_m^* - w_f^*$ (BDT)	135.00	-160.00	-528.00	773.00
$\mathcal{W}_m^E$ ('000 BDT)	-129.39	-129.39	-129.39	-129.39
$\mathcal{W}_m^A$ ('000 BDT)	219.35	219.35	219.35	219.35
$\mathcal{W}_f^E$ ('000 BDT)	-834.18	-188.85	-712.61	-511.03
$\mathcal{W}_f^A$ ('000 BDT)	107.28	226.19	448.92	31.78
Π ('000 BDT)	791.75	901.03	929.17	681.87
Total Cost ('000 BDT)	0.00	316.80	347.49	0.00

Notes: The table shows the results from evaluating the effectiveness of transport and subsidy interventions. We use both employers' and applicants' beliefs about the job costs and productivity of the three industries in our sample. We evaluate the following interventions: 1) female transport paid by the policymaker, 2) a BDT 900 subsidy for hiring female workers paid to the employer, 3) female transport paid by the employer. We present effects on the following outcomes: We present effects on the following outcomes: 1) male and female employment as well as the the gender employment gap, $L_m^*, L_f^*, L_m^* - L_f^*$ (in percentage points), 2) male and female wages as well as the gender wage gap, $w_m^*, w_f^*, w_m^* - w_f^*$ (in BDT), 3) total male welfare as perceived by employers, $\mathcal{W}_m^E$ (in '000 BDT), and applicants, $\mathcal{W}_m^A$ (in '000 BDT), 4) total female welfare as perceived by employers, $\mathcal{W}_f^E$ (in '000 BDT) and applicants, $\mathcal{W}_f^A$ (in '000 BDT), 5) total profits (in '000 BDT), 6) total costs to the implementer (in '000 BDT).