Paternalistic Discrimination*

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We combine two field experiments in Bangladesh with a structural labor model to identify *paternalistic discrimination*, the differential treatment of two groups to protect one group, even against its will, from harmful or unpleasant situations. We observe hiring and application decisions for a night-shift job that provides worker transport at the end of the shift. In the first experiment, we use information about the transport to vary employers' perceptions of job costs to female workers while holding taste-based and statistical discrimination constant: Not informing employers about the transport decreases demand for female labor by 21%. Employers respond more to transport information than cash payments to female workers that enable workers to purchase transport themselves. In the second experiment, not informing applicants about the transport reduces female labor supply by 15%. In structural simulations, paternalistic discrimination has a larger effect on gender employment and wage gaps than taste-based and statistical discrimination.

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1 Introduction

Economists traditionally distinguish between two forms of labor market discrimination: *taste-based discrimination*, a simple preference for hiring one group over the other (Becker, 1957), and *statistical discrimination*, a belief that one group is more productive than the other (Phelps, 1972; Arrow, 1973). However, the standard labor market model does not incorporate other-regarding employers, i.e., employers who care about their workers' wellbeing. Other-regarding employers may attempt to protect workers from physical injury, reputational damage, or long hours away from their families. This protective behavior could be the source of a third form of discrimination: Employers protect one group differently than another, potentially depriving the protected group of opportunities to build important skills and experiences.

In this paper, we define and test for *paternalistic discrimination*: the differential treatment of two groups to protect one group, even against its will, from harmful or unpleasant situations. In the labor market, paternalistic discrimination may lead employers to hire women over men for female-stereotyped jobs, to avoid promoting recent mothers to reduce workloads, or to fire single workers over workers with families.[1] Given global attitudes towards protecting women (Glick et al., 2000), this discrimination could be particularly prevalent against women. Consistently, governments around the world restrict women's employment paternalistically: 49 countries restrict women's work in hazardous jobs and 21 in night jobs (World Bank, 2023a).[2]

We combine a simple model, two field experiments, and structural estimates to measure paternalistic discrimination against women. First, we augment a standard labor market model with other-regarding employers, i.e., employers who value their work-

[1] Outside of the labor market, parents may be more protective of their daughters (Bezirganian and Cohen, 1992; Kuhle et al., 2015) and women may receive different advice about educational pathways, careers, or investments (Bajtelsmit and Bernasek, 1996; Carlana, 2019; Gallen and Wasserman, 2021).

[2] 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 (The Labour Protection Act B.E. 2541, 2014; World Bank, 2023b). Similar laws exist in Argentina, Cameroon, China, India, the Republic of Korea, Saudi Arabia, and other countries (Anand and Kaur, 2022; US Department of State, 2022a,b; World Bank, 2023b). All but 17 countries also ban women from fighting in combat (Fitriani et al., 2016).

ers' welfare. Second, 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. 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 potential labor market interventions.

The key innovation of our model is that employers internalize the welfare of their workers and thus hire fewer workers with a low perceived welfare. Building on traditional models of discrimination, our model incorporates simple distaste (taste-based discrimination), beliefs about profitability (statistical discrimination), and beliefs about worker welfare (other-regarding discrimination) from hiring members of a particular gender. We distinguish between two possible types of other-regarding discrimination, committed by either deferential or paternalistic employers. Deferential employers use *applicants' beliefs and preferences*, such as risk preferences, to evaluate worker welfare, while paternalistic employers use *their own beliefs and preferences for workers* to evaluate worker welfare. Our model yields five predictions, which we evaluate using 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 perceived job costs for workers. We recruit 495 *employers*, individuals with recent hiring experience, in Dhaka, Bangladesh. These employers make 4,950 hiring decisions (10 per employer) between one male and one female applicant for a job created by the research team: a one-time workshop and office job on the night shift. We randomly implement one hiring choice per employer and pay the employer based on the performance of their worker. We randomize whether we inform employers that workers receive free, safe transport home at the end of the shift. We find that employers who are not informed about the transport hire 21% fewer women.

The key feature of our design is that we hold taste-based and statistical discrimination constant across transport treatments. To hold constant the perceived selection of applicants willing to work, and thus taste-based discrimination, we inform employers that all applicants have applied for the job without knowing about the transport. In addition, we show every applicant-pair to several employers, allowing us to test whether information about the transport affects the hiring choices for the same applicant pair. To hold constant the perceived productivity of applicants willing to work, and thus statistical discrimination, we inform employers that workers will only learn about the transport after completing the shift, i.e., that the transport cannot affect their attendance or on-the-job performance.[3] To ensure that differences in hiring are not explained by concerns about the employers' reputation, all hiring choices are private and anonymous.

We experimentally vary payments to workers to test the second theoretical prediction: Deferential employers respond differently from paternalistic employers to providing workers with cash payments and transport. Deferential employers respect workers' beliefs and preferences. Thus, they demand workers weakly more when workers receive sufficient cash to decide whether to purchase safe transport than when workers receive the transport itself. Paternalistic employers, on the other hand, may demand workers less with cash than with transport if they believe that workers *should* purchase the transport but, when given the choice, would not. We cross-randomize employers into one of four cash treatments ("subsidies"): (i) female workers receive a surprise subsidy of 1,000 Bangladesh Taka (BDT, or USD 10)—an amount much larger than standard transport costs in our setting (Uber in Dhaka typically costs less than BDT 500 from our shift site 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 hire women significantly less with the female worker subsidies than the transport—even though workers prefer cash over the transport. This suggests that employers paternalistically prevent workers from making their own choices. Finally, consistent with the third theoretical prediction, employers react significantly more to the employer than either of the worker subsidies.

We assess employer heterogeneity to test our fourth prediction: Demand responds to changes in perceived worker welfare more strongly among other-regarding employers. Employers who score highly in a module on other-regarding preferences toward women react almost four times more to the transport treatment than less paternalistic employers.

Employers' response to information about the transport and female worker subsidies appears to be driven by employers disagreeing with both applicants' *beliefs* about

[3] Note that there are no concerns about worker retention because there is only one shift.

job costs and applicants' *preferences*. Employers report that women underestimate the costs of working at night more than men—even though, in reality, employers overestimate night shift risks to women. Consistent with employers' beliefs, we find the strongest treatment effects against inexperienced women. We also find that 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. Finally, female employers, unlike male employers, do not report that women underestimate the costs of working at night more than men. Female employers also do not react to information about the transport.[4] Overall, these heterogeneous treatment effects offer additional evidence that (male) employers are paternalistic rather than deferential.

We complement the demand-side experiment with a supply-side experiment, in which we randomly vary information about the transport to applicants. We find that randomly withholding information on the transport from potential applicants reduces the supply of female labor by 15%, significantly less than the demand reduction from employers. In particular, the reservation wages of the 770 *applicants*, both male and female, recruited from the same population but distinct from those in the demand-side experiment, increase by about BDT 200 (USD 2), which is much less than employers' valuation of female worker transport of 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 labor demand decreases more than supply. We construct the labor demand function by estimating preference parameters in a binary choice model using the hiring choices in the demand-side experiment. We construct the labor supply function by aggregating the reservation wages in the supply-side experiment. We combine the two functions to construct equilibria for both genders with and without transport in counterfactual markets for our night-shift job.

We find that lack of transport reduces both female employment and wages. We also find that paternalistic discrimination has a greater effect on gender employment and wage gaps than taste-based or statistical discrimination in our setting. However, the welfare effects of eliminating paternalistic discrimination are ambiguous: If employers

[4] However, we consider these results as suggestive given our small sample of female employers.

are well-informed about the dangers on the job, paternalism may help women avoid pitfalls; but if women understand the risks, paternalism may restrict them from accessing beneficial opportunities. We simulate counterfactual policy interventions and find that the welfare effects similarly depend on the accuracy of beliefs about job costs for workers. Transport increases worker welfare more if employers have correct beliefs, while female worker subsidies increase total welfare more if applicants have correct beliefs.

The degree of paternalism revealed in our experiment suggests opportunities to increase female employment and wages in settings with strong gender norms. Although we model other-regarding employers, our model is observationally equivalent to one in which employers *act as if* they internalize workers' welfare to, for example, follow a protective social norm (Boudet, 2013; Jayachandran, 2021) or signal their identity as a protective person (Akerlof and Kranton, 2000).[5] Yet, policies that reduce paternalistic discrimination may also eliminate some self-regarding reasons to discriminate, for example, by eliminating socially acceptable covers for taste-based discrimination. In addition, while previous research has shown that the prevention of work-related dangers and unsafe transportation can increase female labor *supply* (Field and Vyborny, 2022; Cheema et al., 2022; Grosset, 2024), our findings suggest that these policies can also increase *demand* for female labor. This implies that there are compounding benefits from policies that reduce women's perceived job costs (e.g., crime reduction or workplace safety programs) or increase their perceived benefits (e.g., wage laws or subsidies).

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 (e.g., Goldin and Rouse, 2000; Bertrand and Mullainathan, 2004; Levitt, 2004; Gneezy et al., 2012; Glover et al., 2017; Baert, 2018; Bohren et al., 2019; Kessler et al., 2019; Dianat et al., 2022; Kline et al., 2022; Chan, 2022; Macchi, 2023; Adamovic and Leibbrandt, 2023) and describes behavioral foundations of discriminatory beliefs (e.g., Bordalo et al., 2016; Esponda et al., 2023). Paternalistic discrimination differs

[5] One experimental result suggests that employer behavior is not driven strictly by adherence to norms: employers increase female hiring when women receive a surprise cash subsidy. This behavior appears more consistent with our model of other-regarding preferences.

from taste-based discrimination, as it varies with workers' perceived welfare.[6] It also differs from statistical discrimination in two key ways. First, it is driven by other-regarding rather than self-regarding motives—indeed, employers may 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.[7] We consider paternalistic discrimination most closely related to benevolent sexism (Glick and Fiske, 1997) in the psychology literature—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).[8] Our paper draws on the benevolent sexism literature to formalize the first economic model of paternalistic discrimination.[9]

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; Elías et al., 2023), regulating addictive products (e.g., Allcott et al., 2019a,b; DeCicca et al., 2022), and protecting boundedly rational or time-inconsistent consumers (e.g., Allcott and Taubinsky, 2015; Allcott et al., 2021). Research also explored the drivers of and re-

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

[7] Paternalistic discrimination could also result from and induce systemic discrimination (Bohren et al., 2022). Paternalistic discrimination could result from systemic discrimination that drives differences in non-gender characteristics that correlate with gender, such as transport costs. Paternalistic discrimination could induce systemic discrimination by depriving women of opportunities to build important skills and experiences, limiting their human capital accumulation and reducing their promotability later on.

[8] In line with theories of benevolent sexism, economists have found that advisors withhold negative feedback from female advisees (Coutts et al., 2024) and that male evaluators attribute bad outcomes to bad luck more often for women than for men (Erkal et al., 2023).

[9] U.S. law treats benevolent discrimination as any other kind of discrimination (U.S. EEOC, 2007, 2022). A separate but related concept in the law literature is *benign discrimination*, discriminatory policies designed to benefit marginalized groups (see, for example, Evans 1974 and Patty 1989).

sponses to paternalism (Uhl, 2011; Ambuehl et al., 2021; Bartling et al., 2023), and the relationship between paternalism and altruism (Jacobsson et al., 2007). Other-regarding preferences also drive behavior in the workplace, including wage setting (Akerlof, 1982), workers' effort (Bandiera et al., 2005; Asad et al., 2023), resource allocation (Bandiera et al., 2009; Hjort, 2014), hiring (Dhillon et al., 2020) 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 the barriers to female employment, particularly in low-income countries. This literature considers social norms (e.g., Fernández, 2013; Bertrand et al., 2015; Bernhardt et al., 2018, 2019; Bursztyn et al., 2020; Field et al., 2021; McKelway, 2023; Bursztyn et al., 2023; see Jayachandran, 2021 for an overview), safety (Chaudhary et al., 2021; Field and Vyborny, 2022; Siddique, 2022; Becerra and Guerra, 2023), and work location (Ho et al., 2024; Jalota and Ho, 2024). Part of this literature specifically examines how unsafe transport restricts women's physical mobility (e.g., Kondylis et al., 2020; Aguilar et al., 2021; Borker et al., 2022; Field and Vyborny, 2022; Cheema et al., 2022; Christensen and Osman, 2023; Becerra and Guerra, 2023). 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; Islam et al., 2021). This paper is the first to study how paternalism 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 an equilibrium model and evaluates a series of counterfactuals. Section 7 concludes.

2 Theoretical Framework

2.1 Setup

Market Structure We study two markets, one for each gender $g \in \{m, f\}$. A unit mass of price-taking employers, indexed by k, demand labor in the two markets. A unit mass of male ($g = m$) and 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 demanded by employers is given by L_g^D. Wages and the quantity of hired gender g labor are determined in equilibrium. w_m^* and w_f^* are the equilibrium wages that equate labor supply and demand for both genders simultaneously. L_m^* and L_f^* are the equilibrium quantities at these wages.

Workers' Problem Worker i of gender g supplies labor to employer k if the wage w_g offsets the disutility of working $u_i^A(c_{igk})$, where u_i^A is continuously differentiable and monotonically increasing in job costs c_{igk}, with $u_i^A(0) = 0$.[10] The worker's cost $c_{igk} = c_g + c_i + c_{kg}$ is the sum of (i) a gender-specific constant cost c_g, known to the worker and the employer, (ii) the worker-specific cost c_i, known only to the worker, and (iii) the employer-gender-specific cost c_{kg}, known only to the employer. The employer- and worker-specific costs c_{kg} and c_i follow distributions h_g^K and h^I with CDFs H_g^K and H^I and means $\bar{c}_g^K$ and $\bar{c}_g^I$. Workers rely on their cost assessments and do not attempt to learn about the employer-gender-specific costs from employers' hiring decisions.[11] We assume that applications are costless and that the outside option has zero value such that applicant i of gender g supplies labor if and only if:

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

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 additively separable in (i) d_{kg}, the non-pecuniary benefits of hiring gender g labor (i.e., taste), (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}

[10] Following Rabin 2013, we treat utility as linear in the relatively small one-day salaries; we allow agents to have risk preferences over costs which may be at a larger scale (e.g., sexual assault).

[11] This precludes sophisticated workers from applying to costly jobs, anticipating that paternalistic employers will protect them from mistakes. This assumption is consistent with empirical evidence: Anticipating discrimination 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."

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, $\mathcal{W}_{kg}$ (henceforth "welfare").[12] 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.[13] 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 $\mathcal{W}^A_{kg} \geq 0$.

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

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

We denote employers' second-order beliefs about u^A_i by $u^{E:A}_i$ and their own utility over worker costs by u^E_{ki}. $u^{E:A}_i$ and u^E_{ki} follow the same functional form assumptions as u^A_i.

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

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

with $\mathcal{W}_{kg} \in \{\mathcal{W}^{E:A}_{kg}, \mathcal{W}^E_{kg}\}$.[14]

We define discriminatory preferences leading to preferential treatment of men over women for 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 (or less negative) non-pecuniary returns from hiring male than female workers.

[12] Our model is also flexible enough to allow 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}. We do not distinguish between different channels for other-regarding preferences, such as warm glow or guilt aversion; these different sources of other-regarding behavior are observationally equivalent in our model.

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

[14] Assuming the outside option has zero value, equation 2 is the same if the employer internalizes the welfare of *only* hired or of hired *and* non-hired 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 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 female worker. Deferential employers use their perception of workers' perception of worker welfare and paternalistic employers their own perception of worker welfare.

We consider other-regarding distinct from taste-based discrimination because, unlike taste-based discrimination, it varies 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 $\mathcal{W}_{kg}^{E:A} = \mathcal{W}_{kg}^{A}$.[15]

2.2 Comparative Statics in Gender-Specific Costs and Wages

Other-Regarding Employers and Costs An increase in c_g has two effects on employers' other-regarding utility: (i) a *direct effect*: the job cost increases, reducing employers' perception of worker welfare, and (ii) a *selection effect*: workers with smaller worker-specific cost self-select into the job, increasing employers' perception of worker welfare. Holding selection and productivity constant, an increase in gender-specific costs reduces employers' perception of worker welfare and labor demand by other-regarding but not non-other-regarding employers (see appendix A.2 for the derivation).

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

Deferential and Paternalistic Employers and Costs If employers are deferential (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 cash payment that allows them to afford the amenity. Workers are weakly better off receiving the cash payment, as they can use their own valuation

[15] Note that other-regarding discrimination can only lead to restricting the employment opportunities of willing workers as employers cannot force workers to apply who do not want to apply. Furthermore, other-regarding discrimination can persist in repeated markets if employers do not learn about costs (e.g., if they never observe women working the night shift) or disagree with workers' preferences.

of the amenity to decide whether to purchase it. Therefore, if employers demand less labor with the cash payment than the amenity, they must be paternalistic (i.e., they must use their own beliefs or preferences to evaluate worker welfare, $\mathcal{W}_{kg}^{E}$).

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

Other-Regarding Employers and Wages 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 employers' perception of worker welfare, (ii) a *selection effect*: workers with higher worker-specific cost self-select into the job, decreasing employers' perception of worker welfare. Holding selection and productivity constant, an increase in gender-specific wages reduces the labor demand of other-regarding employers (as $\alpha_{kg} < 1$, see appendix A.3 for the derivation).

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} Employers with high worker welfare weights experience a high other-regarding utility loss from gender-specific costs and a smaller loss from wages.

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

2.2.1 Equilibrium Wages

The equilibrium wage response to gender-specific costs depends on the magnitude of the cost elasticity of demand relative to that of supply (appendix A.4). An increase in c_g decreases labor demand and supply, thus reducing the equilibrium labor quantity. However, an increase in c_g can increase or decrease equilibrium wages depending on the relative magnitudes of the demand and supply elasticities. If the elasticity of demand is sufficiently large relative to that of supply, 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 the ratio of the demand and supply elasticities with respect to gender-specific costs is larger than a cutoff that depends on the substitutability of male and female labor and the demand and supply elasticities with respect to wages of the other gender.*

The other gender's equilibrium quantity and wages do not respond to increases in gender-specific costs if male and female workers are additively separable in production, increase if they are substitutes, and decrease if they are complements (appendix B.1).

3 Setting

We empirically test theoretical predictions 1 to 5 in two experiments in Dhaka, Bangladesh. Around 40% of Bangladesh's population lives in urban areas, and about one-sixth 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 are employed versus about 80% of working-age men (World Bank DataBank, 2023). Women work predominantly in agriculture and industrial production, particularly in the garment sector, where they comprise 80% of the workforce, while men work predominantly in services (Farole et al., 2017; Quayyum, 2019). Women also earn less than men, especially in urban areas (USD 171 versus USD 133 per month, BBS (2018)).[16]

Bangladesh's law does not prohibit discrimination based on sex, nor does it require 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 2006 Bangladesh Labour Act lifted a prohibition on women working

[16] 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).

at night, employers are still required to obtain women's consent to work shifts between 8:00 P.M. and 6:00 A.M.; written consent is not required of men. Training opportunities at night are common in Bangladesh, and night-shift work is becoming increasingly common as many outsourcing firms work European or US hours (Mamun et al., 2019).

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; Kabir and Islam, 2023). These problems have led providers to establish women-only bus service in recent years, though these services offer limited routes and hours (Naher, 2022).

4 The Hiring Experiment: Costs & 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: manufacturing, retail/wholesale and services, and education (additional information on these industries is provided in appendix C.1).[17] Enumerators recruit employers in person between April 2023 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 vast majority of employers in our experiment (94%) are men, in line with estimates in the Bangladesh workforce (89% of managers are men (BBS, 2018); see table 1 for overall summary statistics and appendix table E.9 for summary statistics by industry). Employers are, on average, 32 years old, 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

[17] 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," on a scale from 0 to 10. The average response for women was 2.5 in manufacturing, 1.0 in retail and services, and 0.3 in education.

employees, and they have made 27 hiring decisions in the previous three years.

Table 1: Employer Characteristics (N=495)

	Mean	SD
Female (%)	6.3	24.3
Age (Years)	31.5	7.8
Married (%)	58.5	49.3
Children (%)	45.2	49.8
Bachelor's (%)	42.2	49.4
# Male Employees	8.9	24.3
# Female Employees	6.1	41.5
# Hiring Decisions Last 3 Years	27.2	235.4

Notes: The table shows the means and standard deviations of employer characteristics. *Children* is an indicator equal to 1 if the applicant has at least one child. *Bachelor's* is an indicator equal to 1 if the applicant has at least a Bachelor's degree.

"Employers" 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 from 7:00 P.M. to midnight (see appendix figure C.1 for a photograph of the shift), with free and safe worker transport home in private six-seater cars after the shift. One supervisor accompanied each car.[18] The applicant pool consists of 764 male and 575 female applicants aged 18 to 60, recruited at booths on 11 university campuses between February and April 2023.[19] Applicants take a 12-minute Excel screening test incentivized with

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

[19] 579 male and 399 female applicants come from the hiring experiment and 185 male and 176 female applicants from the application experiment (see section 5). In the hiring experiment, 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). Five hiring pairs were excluded from the sample as the male applicant was miscoded as female and one male and one female applicant revoked their consent. One male worker revoked their consent in the application experiment. We recruited on university campuses anticipating a high concentration of job seekers early in their careers, for whom paternalistic discrimination may be particularly consequential. We do not restrict participation to university students.

BDT 2 (USD 0.02) per correct answer for a total of up to BDT 20 (USD 0.2).[20] On average, male and female applicants in the hiring experiment are 24–25 years old, about one-fifth are married, and 12% have children. Female applicants have slightly less work experience but similar education levels and Excel scores (table 2).[21]

Table 2: Applicant Characteristics by Gender in Hiring and Application Experiments

	Hiring Experiment				Application Experiment			
	Male (N=764)		Female (N=575)		Male (N=354)		Female (N=344)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age (Years)	24.8	6.3	23.6	6.0	25.9	7.8	22.9	6.4
Married (%)	19.3	39.5	22.8	42.0	26.3	44.1	23.5	42.4
Children (%)	12.1	32.6	11.8	32.2	18.4	38.8	13.5	34.2
Bachelor's (%)	39.1	48.8	35.7	48.0	14.3	35.1	8.7	28.2
$\leq$ 3 Years Work Exp (%)	80.0	40.0	89.0	31.3	72.1	44.9	88.9	31.4
Excel Screening Score (%)	22.6	12.5	24.5	13.7	24.8	11.5	26.3	12.1

Notes: The table shows the means and standard deviations of characteristics of applicants recruited for the hiring experiment and the application experiment. *Children* is an indicator equal to 1 if the applicant has at least one child. *Bachelor's* is an indicator equal to 1 if the applicant has at least a Bachelor's degree.

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. The experiment is conducted in six stages, which take an average of 64 minutes:

1. **Basic job information**: Employers receive the following information about the hiring process: (i) Applicants have applied for a one-day Excel workshop and job from 7:00 P.M. to 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.

[20] The test was designed based on a scoping survey with 20 employers about desired Excel skills.

[21] The experiment design does not require balance across genders.

2. **Productivity beliefs elicitation**: 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 that each applicant will complete if hired based on first name, gender, marital status, education, years of experience, and Excel screening test score.[22] Employers are informed that two of these applicants are randomly selected for hire (in the application experiment in section 5) and that the employers receive a bonus payment for correctly predicting the productivity of these applicants. Employers guess (i) the probability each applicant shows up to the shift (incentivized using the binarized scoring rule Hossain and Okui 2013), and (ii) the number of completed tasks conditional on attendance (incentivized with BDT 10, USD 0.1, for guesses within 5ppts from the truth).[23]

3. **Transport information randomization**: We randomly vary employers' perception of workers' job costs with two treatments:
   (a) *Transport* (50%): Employers are informed about the transport.
   (b) *No Transport* (50%): Employers are not informed about any transport.

   To hold constant the perceived selection of applicants across treatments, and thus taste-based discrimination, 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, and thus statistical discrimination, 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 attendance or on-the-job performance. To hold constant liability or reputation concerns across treatments, we ensure employers that all hiring choices are private and anonymous. To hold constant beliefs about applicants' beliefs across treatments, we inform employers in both treatments that applicants are not told

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

[23] To reduce the risk of strategic misreporting, we elicit employers' productivity beliefs before randomizing them to a treatment group. We also verify that the predictions of the 495 *Hiring* employers do not differ from 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.

of any benefits beyond the initial job description; *Transport* employers are told explicitly that applicants are not aware of the transport. We verify comprehension with five comprehension questions administered after the treatment assignments. We also find no evidence for information spillovers.[24]

4. **Cost belief elicitation:** We elicit employers' beliefs about the job costs (including commute) for the applicants for whom they also made productivity predictions. Employers report the job costs in terms of danger, unpleasantness, and social acceptability on a scale from 0 to 10. We do not (i) inform employers of applicants' reported costs to reduce anchoring, or (ii) attach experimental incentives to the elicitation to reduce strategic reporting.[25] We find no significant differences between *Hiring* and *Prediction-Only* employers, suggesting that our results are not driven by strategic misreporting to justify hiring.

5. **Subsidy randomization**: Employers are randomized to one of five subsidy treatments that experimentally vary the payoffs to workers and employers:

   (a) *No Subsidy* (40%): All 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%): All workers receive BDT 1,500 (USD 15) for completing the shift. Employers receive BDT 500 (USD 5) if

[24] Only six *No Transport* employers believe applicants will get home by provided transport and the vast majority of *No Transport* employers (98%) believe applicants will use public transport or a ride share (Uber, CNG, Rikshaw). We also started the shifts only after roughly half (57%) of the hiring experiment was completed so that information spillovers are impossible for the first half of the sample.

[25] 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.

their hired worker is a man, and BDT 1,500 (USD 15) if it is a woman.

(e) *Employer Subsidy for Hiring Men* (1%): All 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.

We include the *Employer Subsidy for Hiring Men* [26] and ask employers to draw their treatment assignment on a piece of paper to not signal gender differences in qualification. We also inform employers that workers are surprised by the subsidies after the shift to hold constant perceived selection and productivity.

6. **Hiring**: Employers make hiring decisions for two male–male pairs and ten mixed-gender pairs; female-female pairs are excluded for market realism and statistical power. One mixed-gender pair comes from the application experiment; the remaining 11 pairs are shown to 11 employers each, implementing a different pair per employer and one hiring choice per pair (see appendix figure C.2 for the experimental interface and C.3 for the matching process).

To reduce experimenter demand, we ensure anonymity through private interviews and assign treatments across employers to make it difficult to infer the study purpose.

4.2 Hiring Analysis: Empirical Specification

We identify *within-applicant* differences in hiring across treatments, ruling out a myriad of endogeneity concerns. The transport was stratified by applicant and employer industry. We restrict the sample to the 460 employers who answer all understanding questions correctly (94%). Employer characteristics are balanced across treatments (appendix tables E.1) but employers report basing their hiring decisions more on safety (but not taste, statistical, or reputation concerns) without than with transport. [27]

We estimate the following equation among all female applicants:[28]

[26] We exclude the six employers assigned to the *Employer Subsidy for Hiring Men* treatment.

[27] We observe small differences in perceived revenues across treatments unlikely to drive hiring choices: Employers in the *Female Subsidy* expect women to generate slightly lower revenues: BDT 29, USD 0.3 ($p = 0.04$, appendix table E.2).

[28] 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.

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

where indicator H_{ki} is 1 if employer k hires female applicant i. Indicators NT_k, MS_k, FS_k, and ES_k 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—i.e., female applicant and employer industry—fixed effects.[29] We test:

- Prediction 1: Female labor demand is lower without safe transport: $\beta_1 < 0$.
- Prediction 2: Female labor demand 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 employers are other-regarding. The second prediction implies they are paternalistic. A deferential employer's utility from hiring women is strictly greater in the *No Transport+Female Subsidy* treatment than the *Transport+No Subsidy* treatment because 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).[30] The third prediction implies labor demand is downward sloping in wages.

Finally, we assess heterogeneity in hiring by employer characteristics elicited from employers *after* making their hiring choices:

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

[29] We also control for a vector of male applicant characteristics (Excel screening score, education, work experience, and marriage status) in the prediction pair from the application experiment, in which women were not always compared to the same man.

[30] In interviews with 99 employers, all employers stated that Ubers are safe, easily available, and affordable using the subsidy of BDT 1,000 (USD 10, the highest employer report was below BDT 800, or USD 8). We did not inform employers that workers can use the subsidy to purchase transport from us to avoid deception (since we provide transport to all workers for ethical reasons).

We estimate treatment responses among employers who (i) reported above-median agreement with paternalistic laws in India that restrict women from working at night (on a 0–10 scale with a median of 8); (ii) 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 of 6); (iii) transferred above-median amounts to the female worker in a three-way dictator game between themselves and two external workers (BDT 0–100 with a median of BDT 30 or USD 0.3 to male and female workers); [31] or (iv) reported 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 of 10). We also average the four measures, each standardized by their control mean (Kling et al., 2007).[32]

4.3 Results: Costs & Labor Demand

Consistent with prediction 1, not informing employers about the transport increases perceptions of job costs (by 1.6 points for male and 3.1 points for female applicants; appendix table E.2) and reduces female hires by 21% (−10ppts, $p < 0.01$) from a baseline of 45% (figure 1, bars 1 and 2). The demand reduction for female labor seems to be driven by changes on the intensive rather than the extensive margin: Employers in the *No Transport* treatment hire about one fewer woman, on average ($p < 0.01$, appendix table E.10). Employers respond more strongly to the transport when they are male or the female applicant has a child (appendix figure E.2 although the differences are not statistically significant given the small number of female employers or applicants with children), or has less experience than the male applicant (appendix figure E.3).[33]

Consistent with prediction 2, employers behave paternalistically: They hire women more under the *Transport+No Subsidy* than the *No Transport+Female Subsidy* condition (45% versus 38%, bars 1 and 6, $p = 0.02$). Employers do not hire women without transport—even when women can afford transport themselves. Consistently, 93% agree women should be protected even against their will (6–10 on the Likert scale).

[31] We suppose that the transfers proxy individual-level variation in other-regarding preferences.

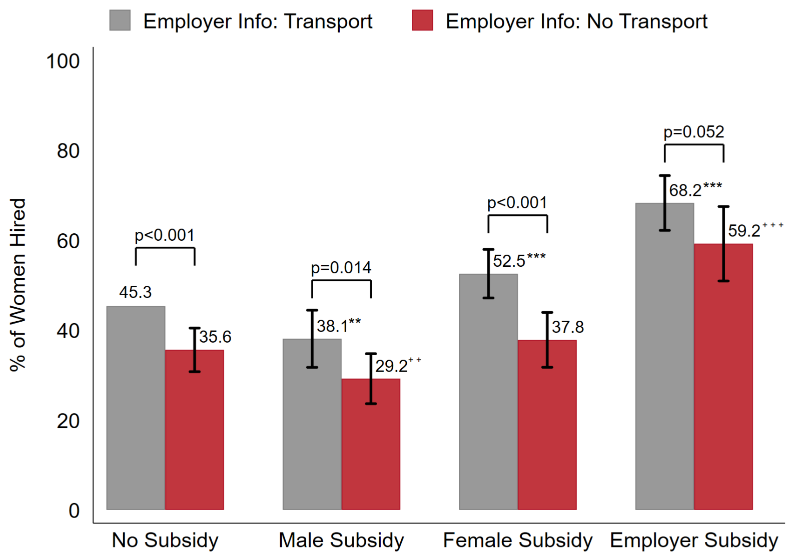
[32] We find similar results when using a correlation-adjusted index (Anderson, 2008).

[33] We also construct causal trees following Athey and Imbens (2016) and find suggestive evidence that employers between the ages of 26 and 32 who have few female employees respond most to the transport treatment. However, these results do not appear to be robust (results not shown; available on request).

The male subsidy increases male hiring with and without transport (+13%, $p = 0.03$, and +10%, $p = 0.04$) and, consistent with prediction 3, the employer subsidy increases hiring more than the worker subsidies with and without transport (+51%, $p < 0.01$, and +66%, $p < 0.01$). Overall, the coefficients on the Excel screening score, the *Female Subsidy*, and the *Employer Subsidy* imply that employers value the transport as much as a 7ppt (0.5SD) increase in the Excel score, BDT 1,351 (USD 14) to the worker, or BDT 424 (USD 4) to the employer (appendix table E.4, columns (1) and (2)).

Results are robust to a series of alternative specifications (see appendix table E.4).

Figure 1: Hiring by Transport Information and Subsidy Assignment



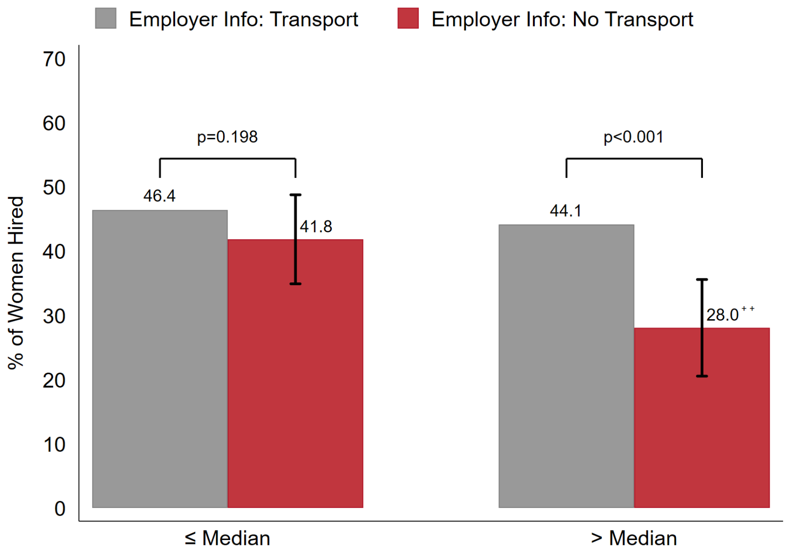
Notes: The graph shows results from equation 3, i.e., the share of women hired by whether the employer knows about the transport or was offered no subsidy, a male or female worker subsidy, or an employer subsidy for hiring women. Each bar is the sum of the control mean and the relevant regression coefficients. 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.[34]

Finally, consistent with prediction 4, employers with stronger other-regarding preferences respond more strongly to the *No Transport* treatment (figure 2, driven largely by employers with strong paternalistic preferences, appendix figure E.1) and direction-

[34] The p-values comparing 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 female with the employer subsidy, with and without transport, are $p < 0.01$ and $p < 0.01$, respectively (not shown).

ally more to the *Female Subsidy* for three out of four measures (appendix figure E.1). These heterogeneity results also suggest that the hiring behavior reflects underlying other-regarding preferences rather than, for example, experimenter demand effects.[35][36]

Figure 2: Hiring by Transport and Other-Regarding Preferences



Notes: We show results from regression 3 run separately among different subsets of employers (see section 4.2). Asterisks are from p-values from Wald tests comparing hiring rates of employers with $\leq$ median and above median other-regarding index with transport, $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$ (on the gray *Transport* bars, only), and pluses from Wald tests comparing hiring rates of employers with $\leq$ median and above median other-regarding index without transport, $p < 0.10^{+}$, $p < 0.05^{++}$, $p < 0.01^{+++}$ (on the red *No Transport* bars, only)

We also find that 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

[35] Furthermore, if experimenter demand effects drive answers to these questions and observed behavior, employers likely perceive protecting women to be the norm, which is consistent with our interpretation of the findings. We do not differentiate between employers who act out of genuine concern, to avoid feeling guilt, or to receive "warm glow" (Andreoni, 1990), consciously or sub-consciously (e.g., through motivated beliefs Bénabou and Tirole (2005)). We consider these forms of other-regarding preferences.

[36] Overall, we do not find substantial heterogeneity in dictator game transfers or agreement that women should be protected, making 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)

(see appendix figure C.3 for the experimental interface).[37] This result is consistent with enumerator reports that employers made an 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 demand effects, reducing the salience of gender should *reduce* paternalistic discrimination.

4.4 Mechanisms

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

Value of Job Costs Employers perceive job costs significantly higher without transport than with, and more so for women than men. We elicited first- and second-order beliefs about job costs from 80 *Beliefs-Elicitation* employers for eight applicants from the application experiment (second-order beliefs were incentivized with BDT 5, or USD 0.05, per correct answer).[38] Controlling for other characteristics, employers believe that 56% of women and 31% of men underestimate the value of job costs ($p < 0.01$) and that the average conditional mistake (difference between first- and second-order beliefs) is 1.8 for women and 1.4 for men ($p < 0.01$).

In addition, we find that employers *overestimate* the frequency of negative events experienced on the night shift. 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.

Risk Preferences Employers who believe *women should be* relatively risk-averse reduce hiring significantly more without transport, but not employers who believe *women*

[37] 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.

[38] These employers are different from the 80 *Prediction-Only* employers who made predictions.

are relatively risk-averse (see appendix figure E.4), offering additional evidence that employers are paternalistic rather than deferential. 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]?"[39]

Selection Neglect We find no evidence that selection neglect drives our results. We elicited employers' perceptions of differences in job costs reported by applicants willing and unwilling to take the job at BDT 1,500 (USD 15) in the application experiment.[40] We find that employers overestimate the reported cost differences (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 does not vary with the perceived difference (see appendix figure E.4).

5 The Application Experiment: Costs & Labor Supply

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 Dhaka in March and April 2023. Applicants are similar to those in the hiring experiment (see table 2).

5.1 Application Experiment Design

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

1. **Applicant screening:** Applicants take the Excel screening test and are informed that the workshop and job will be from 7:00 P.M. to midnight and all hired workers receive an Excel certificate of completion (see section 4.1).

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

[40] If selection neglect drives discrimination by causing employers to evaluate the selected pool of willing applicants as if they were a random draw from the population, employers who underestimate the cost differences would respond more strongly to treatment (see, for example, Exley and Nielsen (2024)).

2. **Transport information randomization:** We randomize applicants into:[41]
   (a) *Transport:* Applicants are informed about the safe transport home.
   (b) *No transport:* Applicants are not informed about the safe transport home.

3. **Cost belief elicitation:** We elicit applicants' job costs beliefs (see section 4.1).

4. **Reservation wage elicitation:** We elicit applicants' reservation wages using the Becker–DeGroot–Marschak mechanism (Becker et al. (1964), see appendix figure C.4 for the experimental interface and appendix table C.1 for the random wage distribution). Applicants draw a random wage between BDT 100 (USD 1) and BDT 5,000 (USD 50) by selecting a slip of paper.[42] In total, 231 men and 183 women are hired as part of the application experiment.

5.2 Application Analysis: Empirical Specification

We next 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) and winsorize reservation wages at the 95th percentile (results are robust to not winsorizing). Applicant characteristics are balanced across treatments (appendix table E.5).

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

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

[41] In addition, we 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 are promoted. In the *Low (High) Promotion* arm, promotions are conducted automatically, selecting the 10% (90%) highest-scoring workers.

[42] Applicants are informed about the wages in the distribution but not the probability of drawing each wage. We noticed a correlation between the random lottery wage and applicant characteristics mid-survey. Women, educated applicants, and married applicants without children drew higher random wages on average. We were concerned that enumerators might be redrawing 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.

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, including the applicant's age, Excel screening score, education, years of experience, and marital status.[43] ϵ_i are robust standard errors.

5.3 Results: Costs & Labor Supply

Not informing applicants about the transport increases perceived job costs by 0.4 points for male and 0.8 points for female applicants (appendix table E.5). It further increases the reservation wage of male applicants by 35% (BDT 168, USD 2, $p = 0.07$) from a baseline of BDT 478 (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 3). Women's high reservation wage with transport is consistent with women's higher perceived costs even with transport. Interestingly, male and female applicants' transport valuation is similar to the expected local transport price in Dhaka (CNG, Rikshaw, based on our survey with 99 employers). By contrast, employers value female workers' transport significantly more, at BDT 1,351 (USD 14, $p < 0.01$, section 4.3). At the hiring experiment wage (BDT 1,500, USD 15), male labor supply decreases by 5% (4ppts, $p > 0.1$) without transport and female labor supply by 15% (13ppts, $p = 0.06$, appendix table E.6). Results are robust to a series of alternative specifications (appendix table E.6).

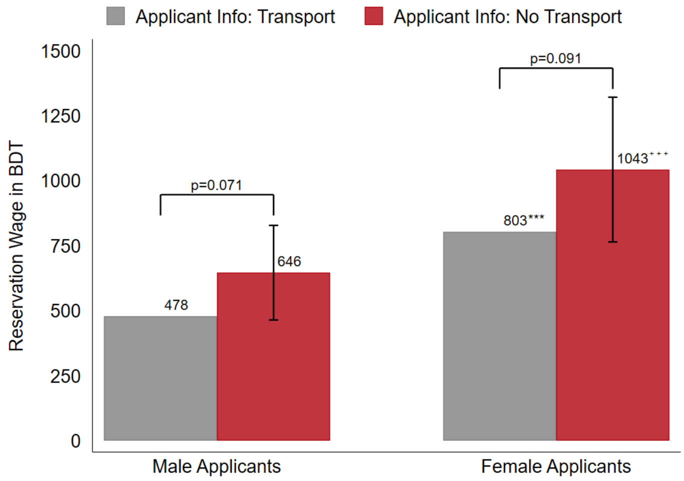
6 Structural Estimation: Costs & Market Equilibrium

To quantify the effect of paternalistic discrimination on equilibrium employment and wages and explore prediction 5, we combine the results from the labor demand and supply experiments described in an equilibrium model. First, we construct the labor demand function using employers' decisions in the hiring experiment, allowing worker selection and expected productivity to vary in perceived job costs. Second, we estimate labor supply using applicants' reservation wages in the application experiment. Third, we combine demand and supply to identify equilibrium employment and wages for men and women. Finally, we benchmark the importance of paternalistic discrimination

[43] 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 41).

in our setting and assess the effectiveness of transport and subsidy interventions.

Figure 3: Reservation Wages 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). Within-gender comparisons of reservation wages with and without transport are given by p-values above bars.

6.1 Labor Demand

We construct the labor demand in three steps. First, we estimate employers' preferences, i.e., how employers trade off taste, profit, and other-regarding concerns. Second, we estimate how employers' beliefs about worker productivity and welfare vary in wages and transport. Third, we use the estimated preferences and predicted beliefs to simulate labor demand in counterfactual markets for male and female workers.

6.1.1 Parametrization

Following equation 2, employer k's expected utility from hiring applicant i of gender g in industry j at wage w_{jg} and without transport $NT \in \{0, 1\}$ is given by:

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

where v_{ki} is the utility that varies with the applicant's gender, expected profit, and other-regarding utility, and $\varepsilon_{ki} \sim EV1$ is an unobserved demand shock. The employer's *preferences* are given by taste parameter d_j, preference for profits β_j, and other-regarding utility weights α_{jg}. The employer's *beliefs* about the worker's profitability and welfare are given by $\Pi_{ki}(w_{jg}, NT_{jg}) = Y^E(\hat{Y}_{kf}(w_{jf}, NT_{jf}), \hat{Y}_{km}(w_{jm}, NT_{jm})) - L_{kf}w_{jf} - L_{km}w_{jm}$ and $\mathcal{W}^E_{ki}(w_{jg}, NT_{jg}) = w_{jg} - c^E_{kg}(w_{jg}, NT_{jg})$, where Y^E are the employer's expected earnings as a function of perceived female ($\hat{Y}_{kf}(w_{jf}, NT_{jf})$) and male ($\hat{Y}_{km}(w_{jm}, NT_{jm})$) productivity and $c^E_{kg}(w_{jg}, NT_{jg})$ are the employer's expected job costs of gender g applicants.

6.1.2 Estimating Employers' Preferences

We estimate preference parameters $(d_j, \beta_j, \alpha_{jm}, \alpha_{jf})$ in a logit model via maximum likelihood.[44] The probability that employer k from industry j chooses to hire applicant i over applicant i' is determined by the relative utility of hiring each applicant:

$$P_{kii'} = \Pr(u_{ki} > u_{ki'}) = \frac{exp(v_{ki})}{exp(v_{ki}) + exp(v_{ki'})} \tag{6}$$

where v_{ki} is the non-random utility of employer k from hiring applicant i in equation 5.

We estimate equation 5 using the predicted profits, Π_{ki}, and welfare, $\mathcal{W}^E_{ki}$ by the *Hiring* employers (section 4.1, steps 2 and 4). We present results in money-metric utility by dividing d_j, α_{jm} and α_{jf} by β_j. We estimate standard errors via bootstrap.

Employers' expected profits Π_{ki} are the sum of the employers' base pay of BDT 500 (USD 5), the piece rate of BDT 5 (USD 0.05) multiplied with the predicted number of tasks completed (the incentivized expected attendance rate multiplied by the incentivized expected conditional number of tasks completed; see section 4.1, step 2), and any employer subsidy, BDT 1,000 (USD 10) for female workers in the *Employer Subsidy* treatment and BDT 0 (USD 0) for all other workers.

We calculate $\mathcal{W}^E_{ki}$ as the difference between the worker wage and the expected job costs. Male and female workers in the *No Subsidy* and *Employer Subsidy* treatments receive BDT 1,500 (USD 15) and male workers in the *Male Subsidy* treatment and female

[44] We describe the estimation strategy and alternative specifications in appendix D. We show robustness to alternative modeling approaches in appendix E.5.

workers in the *Female Subsidy* treatment receive BDT 2,500 (USD 25). The expected job costs are the predicted job costs (see section 4.1, step 4) converted to money-metric using conversion rates calculated from employers' hiring responses to costs and worker wages (described in appendix section D.1). We assume that the predicted costs reflect both beliefs about job costs and employers' preferences over these costs.[45]

Parameter Estimates Employers internalize 11% of payments to male workers and 17% of payments to female workers, and place similar weights on the welfare of male and female workers (table 3).[46] We also observe a statistically insignificant distaste for hiring women relative to men (d_j). Holding productivity and worker welfare constant, employers are willing to forego BDT 115 (USD 1) to hire a man rather than a woman. Results are robust to a series of alternative specifications (appendix figure E.5).

Table 3: Employer Preferences: Parameter Estimates

	Pooled	**Manufacturing**	**Services**	**Education**
d	-0.115	-0.024	-0.078	-0.190
	(0.085)	(0.139)	(0.528)	(0.120)
α_m	0.111*	0.011	0.256	0.134
	(0.058)	(0.089)	(0.771)	(0.089)
α_f	0.174***	0.175**	0.253	0.149*
	(0.045)	(0.074)	(0.617)	(0.081)
p-val ($\alpha_m = \alpha_f$)	0.393	0.155	0.997	0.901
Observations	1,816	606	588	622

Notes: The table presents parameter estimates from a logit model (equation 6). The sample includes the four applicants with predictions for the 460 employers who answer all understanding questions correctly and are not assigned to the *Employer Subsidy for Hiring Men*. We exclude 14 applicants in pairs with miscoded genders and 10 in pairs with revoked consent. Our total sample is 1,816 applicants. We control for Excel screening score, education, work experience, and marriage status. All estimates in money metric. d in '000 BDT. Standard errors estimated bootstrap. p-values from testing whether α_m is statistically different from α_f. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

[45] Neither predicted productivity nor costs differ between *Hiring* and *Prediction-Only* employers (see section 4.1, step 2, and appendix table E.3), alleviating concerns that employers may try to hide taste-based behind statistical or paternalistic concerns by understating productivity or overstating costs.

[46] Estimated welfare weights are lower than those estimated by Chen and Li (2009) (0.32–0.47).

6.1.3 Predicting Employer Beliefs as a Function of Wage and Transport

We estimate the beliefs of employers in industry j about productivity, $\hat{Y}_{jg}(w_{jg}, NT_{jg})$ and costs, $c^E_{jg}(w_{jg}, NT_{jg})$, of gender g workers as a function of wage and transport, i.e., allowing beliefs to vary in applicant selection and productivity. We assume homogeneous beliefs for all employers in a given industry (and thus drop subscript k).

To identify the relationship between beliefs, wages, transport, and worker and employer characteristics, we estimate a random forest model in the sample of *Beliefs-Elicitation* employers who each predicted the productivity and costs of eight applicants from the application experiment (see section 4.4). In addition to the information provided to *Hiring* employers (gender, Excel screening score, education, work experience, and marital status), the *Beliefs-Elicitation* employers were also provided with the applicants' wage and transport conditions and informed that these were able to affect selection and productivity in the application experiment. We then use the trained random forest to predict the productivity and costs beliefs of *Hiring* employers in each industry at every wage with and without transport based on the characteristics of the workers willing to work at each given wage and transport condition in the application experiment (see appendix D.3 for additional detail). That is, we answer the question "What would the *Hiring* employers have thought about the applicant if we would have allowed wages and information about the transport to affect selection and productivity?"

6.1.4 Constructing the Labor Demand Curve

Finally, we use the estimated preference parameters and predicted beliefs to simulate labor demand $\widehat{L^D_g}(w_{jg}, NT_{jg})$ as the fraction of gender g workers demanded at wage w_{jg} with and without transport $NT_{jg} \in \{0, 1\}$ in each industry. As in the experimental set-up, each market consists of 495 employers and 495 workers (either male or female). Each employer chooses how many male and female workers to hire and receives zero taste, profit, or other-regarding utility from any unhired applicant. We assume that the employers' expected revenues follow a constant-elasticity-of-substitution (CES) earnings function that takes as input the expected female ($\hat{Y}_{jf}$) and male ($\hat{Y}_{jm}$) productivity and derive the male and female labor demanded from the employers' first-order conditions (see appendix D.4 for the derivation and parameter selection).

6.2 Labor Supply

We estimate labor supply $\widehat{L_g^S}(w_{jg}, NT_{jg})$ non-parametrically as the fraction of gender g workers with reservation wages $< w_{jg}$ with and without transport $NT_{jg} \in \{0, 1\}$.

6.3 Counterfactuals

We conduct three sets of counterfactual analyses: (i) equilibria with and without transport; (ii) equilibria eliminating various sources of gender disparities; and (iii) equilibria under policy interventions. We consider three outcomes: worker welfare according to applicants, worker welfare according to employers, and profits.[47]

6.3.1 Counterfactual I: Baseline Equilibrium

Not offering transport to applicants reduces equilibrium female employment by 41% (from 75% to 44%) and wages by 52% (from BDT 1085 to BDT 516; figure 4; we present results by industry in appendix figure E.7). In addition, not offering transport reduces male employment by 9% and wages by 24%. Note that the large reductions in employment and wages reflect both profit and other-regarding concerns, as employers believe workers are less productive without transport (in terms of show-up rates and number of tasks completed). Consistent with prediction 5, as the demand response to transport is larger than the supply response, not offering transport still reduces equilibrium female (but not male) employment and wages even when holding constant selection and productivity across transport conditions (appendix figure E.6).

6.3.2 Counterfactual II: Benchmarking Paternalistic Discrimination

We consider a series of counterfactuals that one-by-one eliminate:

1. Paternalistic discrimination: Equalize other-regarding utility by setting female (i) welfare weights to that of men ($\alpha_{jf} = \alpha_{jm} = \widehat{\alpha_{jm}}$), (ii) expected welfare ($\mathcal{W}_{jf}^E(w) = \mathcal{W}_{jm}^E(w) = \widehat{\mathcal{W}^E}_{jm}(w)$), or (iii) both welfare weights and welfare

[47] We use employers' beliefs about welfare and profits because the true values are not observed.

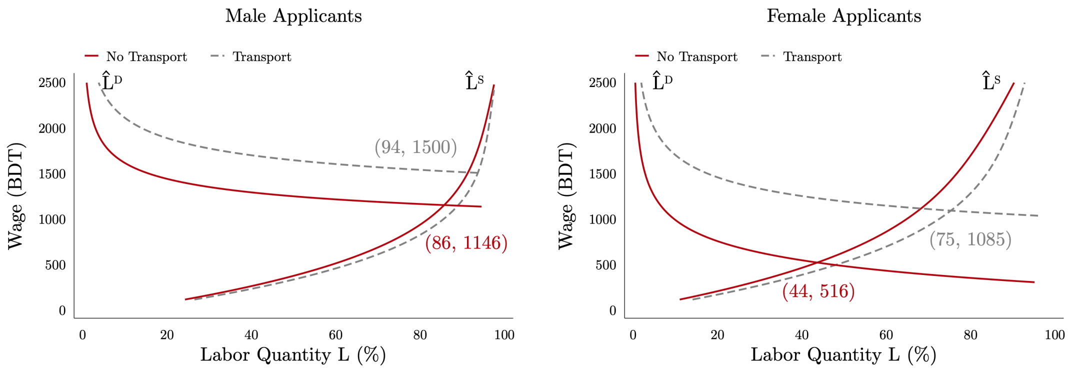
$(\alpha_{jf}\mathcal{W}^E_{jf}(w) = \alpha_{jm}\mathcal{W}^E_{jm}(w) = \widehat{\alpha_{jm}}\widehat{\mathcal{W}^E}_{jm}(w))$. We present welfare results under employers' status quo beliefs.[48]

2. Taste-based discrimination: Set non-pecuniary returns to zero $(d_j = 0)$.

3. Statistical discrimination: Equalize the expected profit at every wage by setting expected female profits to that of men $\left(\Pi^E_{jf}(w) = \Pi^E_{jm}(w) = \widehat{\Pi^E}_{jm}(w)\right)$.

4. Differences in labor supply: Equalize labor supply at every wage by setting female labor supply to that of men $(L^S_f(w) = L^S_m(w) = \widehat{L^S}_m(w))$.

Figure 4: Equilibria in the Male and Female Labor Markets



Notes: The graph shows the share of workers demanded and supplied in male and female labor markets at each wage 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 the CES production function described in appendix D.4. Numbers in parentheses in the graph give (L^*_g, w^*_g). Numbers in gray on top are the equilibrium with transport and numbers in red in the bottom are the equilibrium without transport.

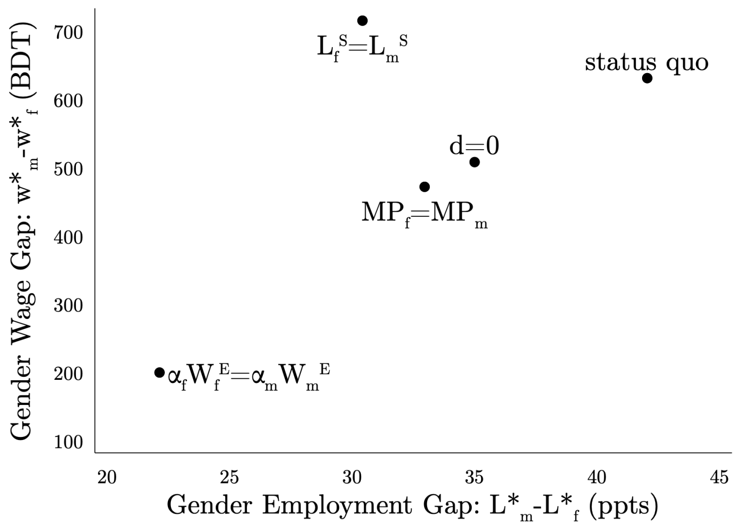
Benchmarking Results Paternalistic discrimination drives a larger share of the gender and wage gaps than statistical and taste-based discrimination in our experimental setting (figure 5). Eliminating paternalistic discrimination reduces the gender employment gap by 48% (20ppts) and the gender wage gap by 68% (BDT 431 or USD 4.3, appendix table E.11). In addition, it *reduces* worker welfare by 16% using employers' perceptions but *increases* worker welfare by 35% using workers' own perceptions.

By contrast, eliminating taste-based and statistical discrimination reduces the gender employment gap by 17% (7ppts) and 21% (9ppts) and the gender wage gap by 19%

[48] Employers in the simulation behave as if they have the same beliefs and preferences toward men and women, but we evaluate employers' perceptions of worker welfare using employers' original beliefs.

(BDT 123 or USD 1.2) and 25% (BDT 160 or USD 1.6), respectively, while eliminating differences in labor supply reduces the gender employment gap by 29% (12ppts) 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 setting since the night shift is highly salient and taste-based and statistical discrimination might be relatively small as employers do not work with applicants and receive a highly informative productivity signal (the Excel screening score).

Figure 5: 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 4) as well as in four different counterfactuals that eliminate one-by-one: 1) paternalistic discrimination $\left(\alpha_f \mathcal{W}_f^E = \alpha_m \mathcal{W}_m^E\right)$, 2) taste-based discrimination ($d = 0$), 3) statistical discrimination $\left(\Pi_f^E = \Pi_m^E\right)$, and 4) differences in labor supply $\left(L_f^S = L_m^S\right)$.

6.3.3 Counterfactual III: Policy Interventions

Finally, we consider the welfare effects and cost effectiveness of two counterfactual policies in our setting: safe transport or hiring subsidies for female workers.

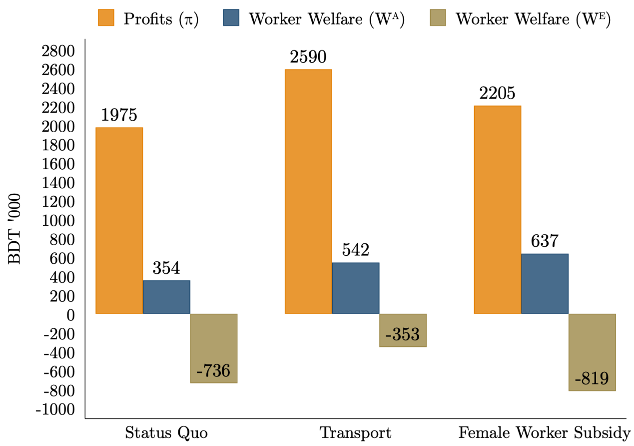
Safe Transport for Female Workers We estimate the welfare effects and financial cost of providing safe transport to female workers at a cost to the policymaker of BDT 800 (USD 8) for each woman hired — the cost of a private car service in our setting.

Female Subsidy We estimate the effects of providing female workers a subsidy s. Labor is supplied at each wage w^E by all female workers willing to work at the wage

$w^A = w^E + s$. The labor demand 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. We use the subsidy that equalizes the policymaker's expenditures, amounting to BDT 791 (USD 8) per woman hired.

Policy Intervention Results Employers believe that the transport intervention results in a larger increase in expected profits (BDT 615k, USD 6,150) and worker welfare (BDT 383k, USD 3,830) than the subsidy intervention (BDT 230k, USD 2,300 and –BDT 83k, –USD 830) while workers believe that the subsidy intervention results in a larger increase in worker welfare (BDT 283k, USD 2,830) than the transport intervention (BDT 189k, USD 1,890; figure 6 and appendix table E.12).

Figure 6: Welfare Effects of Transport and Subsidy Interventions



Notes: The figure shows total expected profits and 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, a counterfactual equilibrium in which female workers receive free transport and a counterfactual equilibrium in which female workers receive a subsidy of BDT 791 (USD 8). Results in BDT $'000$.

7 Conclusion

Combining a labor market model with data from two parallel field experiments, this paper considers paternalism as a source of labor market discrimination.

Paternalistic discrimination implies that decreasing workers' job costs or increasing workers' benefits may increase both the supply of and demand for labor. Meanwhile, programs targeting women's labor supply may be more effective if they simultaneously address demand-side constraints.

Our data suggest that women with little experience suffer the most from paternalistic discrimination. Obstacles to early-career employment may keep these applicants off the career ladder, slowing human capital accumulation and eliminating future opportunities. 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 girls and boys' preferences during their most formative stages. Finally, paternalistic discrimination can even lead to a "minority trap" (Balboni et al., 2022; Cabral, 2022) where a disadvantaged group is discriminated due to the very costs related to being disadvantaged, reinforcing the disadvantaged status.

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A Theory Appendix

A.1 Production Function

We make the following production function assumptions to ensure a unique solution to the employer's problem. The CES production function satisfies these assumptions.

1. $Y^E(L_{kf}, L_{km})$ is a non-negative, continuously twice-differentiable function.
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}.

A.2 Derivation of Prediction 1

The welfare response to an increase in gender-specific costs c_g is given by:

$$\frac{\partial \mathcal{W}_{kg}}{\partial c_g} = -\frac{\partial}{\partial c_g}\mathbb{E}_k[u_{ki}(c_g + c_i + c_{kg})\,|\mathbb{E}_i[u_i^{E:A}(c_g + c_i + c_{kg})] \leq w_g], \tag{7}$$

for $u_{ki} \in \{u_{ki}^E, u_i^{E:A}\}$. A change in job costs has two effects: (i) *direct*: job costs increase, reducing the employer's perception of applicant welfare, and (ii) *selection*: workers with smaller individual job costs self-select into the job, partially offsetting the increase in perceived job costs. With selection fixed, $\frac{\partial \mathcal{W}_{kg}}{\partial c_g} < 0$.

The first-order conditions implied by the employer's problem (equation 2) are:

$$\begin{aligned} \underset{L_{kf}}{FOC} \quad & d_{kf} + \frac{\partial Y^E(L_{kf}, L_{km})}{\partial L_{kf}} + \alpha_{kf}\mathcal{W}_{kf} - w_f = 0 \\ \underset{L_{km}}{FOC} \quad & d_{km} + \frac{\partial Y^E(L_{kf}, L_{km})}{\partial L_{km}} + \alpha_{km}\mathcal{W}_{km} - w_m = 0. \end{aligned} \tag{8}$$

Given production function assumptions 1–4, the above system of equations has a unique maximum. Implicit differentiation yields the following comparative static:

$$\frac{\partial L_{kf}}{\partial c_f} = -\frac{\alpha_{kf} \overbrace{\frac{\partial \mathcal{W}_{kf}}{\partial c_f}}^{<0} \overbrace{\frac{\partial^2 Y^E}{\partial L_{km}^2}}^{<0}}{\underbrace{\frac{\partial^2 Y^E}{\partial L_{kf}^2}\frac{\partial^2 Y^E}{\partial L_{km}^2} - \left(\frac{\partial^2 Y^E}{\partial L_{km}\partial L_{kf}}\right)^2}_{>0}} \tag{9}$$

This is equal to 0 if and only if $\alpha_{kf} = 0$, > 0 if and only if $\alpha_{kf} < 0$ and less than 0 if and only if $\alpha_{kf} > 0$. The results are equivalent for $\frac{\partial L_{km}}{\partial c_m}$.

A.3 Derivation of Prediction 3

The welfare response to increases in gender-specific wages w_g is given by:

$$\frac{\partial \mathcal{W}_{kg}}{\partial w_g} = 1 - \frac{\partial}{\partial w_g}\mathbb{E}_k[u_{ki}(c_i + c_{kg} + c_g)|\mathbb{E}_i[u_i^{E:A}(c_i + c_{kg} + c_g)] \leq w_g], \tag{10}$$

for $u_{ki} \in \{u_{ki}^E, u_i^{E:A}\}$. With selection fixed, $\frac{\partial \mathcal{W}_{kg}}{\partial w_g} > 0$. Implicit differentiation of the first-order conditions 8 yields the following comparative static:

$$\frac{\partial L_{kf}}{\partial w_f} = \frac{\overbrace{\frac{\partial^2 Y^E}{\partial L_{km}^2}}^{<0}(1-\alpha_{kf})}{\underbrace{\frac{\partial^2 Y^E}{\partial L_{kf}^2}\frac{\partial^2 Y^E}{\partial L_{km}^2} - \left(\frac{\partial^2 Y^E}{\partial L_{km}\partial L_{kf}}\right)^2}_{>0}} \tag{11}$$

The above is ≥ 0 if and only if $\alpha_{kf} \geq 1$. The results are equivalent for $\frac{\partial L_{km}}{\partial w_m}$.

A.4 Derivation of Prediction 5

We calculate the cross-wage elasticity of male labor demand with respect to female wages. Male and female workers are substitutes if the elasticity is positive, complements if it is negative, and neither substitutes nor complements if it is 0.

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

Thus, $\epsilon_{w_f,w_m} > 0$ if and only if $\frac{\partial^2 Y^E}{\partial L_{km}\partial L_{kf}} < 0$, $\epsilon_{w_f,w_m} < 0$ if and only if $\frac{\partial^2 Y^E}{\partial L_{km}\partial L_{kf}} > 0$ and $\epsilon_{w_f,w_m} = 0$ if and only if $\frac{\partial^2 Y^E}{\partial L_{km}\partial L_{kf}} = 0$.

Implicit differentiation of the first-order conditions 8 yields:

$$\frac{\partial L_{km}}{\partial c_f} = \frac{\alpha_{kf}\overbrace{\frac{\partial \mathcal{W}_{kf}}{\partial c_f}}^{<0}\overbrace{\frac{\partial^2 Y^E}{\partial L_{km}\partial L_{kf}}}^{?}}{\underbrace{\frac{\partial^2 Y^E}{\partial L_{kf}^2}\frac{\partial^2 Y^E}{\partial L_{km}^2} - \left(\frac{\partial^2 Y^E}{\partial L_{km}\partial L_{kf}}\right)^2}_{>0}}. \tag{13}$$

Assuming $\alpha_{kf} \geq 0$, the above is 0 if $\alpha_{kf} = 0$ or if $Y^E_{L_{km},L_{kf}} = 0$, i.e., male and female workers are neither substitutes nor complements. For $\alpha_{kf} > 0$, it is < 0 if $Y^E_{L_{km},L_{kf}} > 0$, i.e., male and female workers are complements, and > 0 if $Y^E_{L_{km},L_{kf}} < 0$, 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 fewer male workers if they are complements.

Let c_i follow distribution h^I_g, which is a continuously differentiable density function with no mass points. The supply of gender g labor is then:

$$L_g = L^S_g \equiv \int_i \mathbb{1}\left(\mathbb{E}_i[u^A(c_i + c_{kg} + c_g)] \leq w_g\right) h^I_g(c_i)dc_i \tag{14}$$

As $\frac{\partial Y^E(L_{kf},L_{km})}{\partial L_{kg}}$ is a continuous function that increases monotonically in L_{kg} for $g \in \{f, m\}$, the inverse function $\left(\frac{\partial Y^E(L_{kf},L_{km})}{\partial L_{kg}}\right)^{-1}$ exists. The demand for gender g labor is then given by the following equation:

$$L_g = L^D_g \equiv \int_k \left(\frac{\partial Y^E(w_g - d_{kg} - \alpha_{kg}\mathcal{W}_{kg}, L_{kg'})}{\partial L_{kg}}\right)^{-1} dk, \tag{15}$$

The system of equations given by 14 and 15 then describes the equilibrium.

This system has a local solution if it has continuous partial derivatives with respect to all endogenous and exogenous variables and a non-zero Jacobian:

$$\begin{bmatrix} 1 & 0 & -\frac{\partial L_f^S}{\partial w_f} & 0 \\ 0 & 1 & 0 & -\frac{\partial L_m^S}{\partial w_m} \\ 1 & 0 & -\frac{\partial L_f^D}{\partial w_f} & -\frac{\partial L_f^D}{\partial w_m} \\ 0 & 1 & -\frac{\partial L_m^D}{\partial w_f} & -\frac{\partial L_m^D}{\partial w_m} \end{bmatrix} \begin{bmatrix} \frac{\partial L_f^*}{\partial c_f} \\ \frac{\partial L_m^*}{\partial c_f} \\ \frac{\partial w_f^*}{\partial c_f} \\ \frac{\partial w_m^*}{\partial c_f} \end{bmatrix} = \begin{bmatrix} \frac{\partial L_f^S}{\partial c_f} \\ 0 \\ \frac{\partial L_f^D}{\partial c_f} \\ \frac{\partial L_m^D}{\partial c_f} \end{bmatrix} \tag{16}$$

The following equation gives the determinant of the Jacobian:

$$|J| = \underbrace{\left(\frac{\partial L_f^D}{\partial w_f}\frac{\partial L_m^D}{\partial w_m} - \frac{\partial L_f^D}{\partial w_m}\frac{\partial L_m^D}{\partial w_f}\right)}_{=(1-\alpha_{kf})(1-\alpha_{km})>0} \underbrace{+\frac{\partial L_f^S}{\partial w_f}\left(\frac{\partial L_m^S}{\partial w_m} - \frac{\partial L_m^D}{\partial w_m}\right)}_{>0} \underbrace{-\frac{\partial L_f^D}{\partial w_f}\frac{\partial L_m^S}{\partial w_m}}_{>0}$$

Thus, as the Jacobian is positive, the system of equation has a solution.

Next, we show how the equilibrium 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 with the solution to the system. As we already know that $|J| > 0$, we only sign $|J_j|$.

To evaluate the sign of $\frac{\partial L_f^*}{\partial c_f} = \frac{|J_1|}{|J|}$, we calculate $|J_1|$ and re-arrange:

$$\begin{aligned} |J_1| = &\underbrace{\frac{\partial L_f^S}{\partial c_f}}_{<0}\left(\underbrace{\frac{\partial L_f^D}{\partial w_f}\frac{\partial L_m^D}{\partial w_m} - \frac{\partial L_f^D}{\partial w_m}\frac{\partial L_m^D}{\partial w_f}}_{(1-\alpha_{kf})(1-\alpha_{km})>0} \underbrace{-\frac{\partial L_f^D}{\partial w_f}\frac{\partial L_m^S}{\partial w_m}}_{>0}\right) \\ &\underbrace{-\frac{\partial L_f^S}{\partial w_f}}_{<0}\left(\underbrace{\frac{\partial L_f^D}{\partial c_f}\frac{\partial L_m^D}{\partial w_m} - \frac{\partial L_f^D}{\partial w_m}\frac{\partial L_m^D}{\partial c_f}}_{-(1-\alpha_{km})\alpha_{kf}\frac{\partial w_f}{\partial c_f}>0} \underbrace{-\frac{\partial L_f^D}{\partial c_f}\frac{\partial L_m^S}{\partial w_m}}_{>0}\right) < 0 \end{aligned} \tag{17}$$

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 for $\frac{\partial L_m^*}{\partial c_m}$.
To evaluate the sign of $\frac{\partial w_f^*}{\partial c_f} = \frac{|J_3|}{|J|}$, we calculate $|J_3|$ and re-arrange:

$$|J_3| = \underbrace{\frac{\partial L_f^D}{\partial w_m}\frac{\partial L_m^D}{\partial c_f}}_{>0} + \underbrace{\left(\frac{\partial L_m^D}{\partial w_m} - \frac{\partial L_m^S}{\partial w_m}\right)}_{<0}\underbrace{\left(\frac{\partial L_f^S}{\partial c_f} - \frac{\partial L_f^D}{\partial c_f}\right)}_{?} \tag{18}$$

We define $r_{w_m} \equiv \frac{\frac{\partial L_m^S}{\partial w_m}}{\frac{\partial L_m^D}{\partial w_m}} < 0$ as the ratio of the supply and demand elasticities with respect to male wages and $r_{w_m}^D \equiv \frac{\frac{\partial L_f^D}{\partial w_m}}{\frac{\partial L_m^D}{\partial w_m}}$ and $r_{c_f}^D \equiv \frac{\frac{\partial L_m^D}{\partial c_f}}{\frac{\partial L_f^D}{\partial c_f}}$ as the ratio of the demand elasticities with respect to male wages and female costs. Rearranging equation 18, we find that equilibrium wages *decrease* if and only if:

$$\left|\frac{\partial L_f^S}{\partial c_f}\right| < \delta \left|\frac{\partial L_f^D}{\partial c_f}\right| \qquad \text{where } \delta \equiv 1 - \frac{r_{w_m}^D r_{c_f}^D}{1 - r_{w_m}} \in (0,1]. \tag{19}$$

Equilibrium wages decrease if the shift in labor demand shift is proportionally larger than that of supply. The ratios $r_{w_m}^D$ and $r_{c_f}^D$ estimate the labor demand response of the other gender to changes in wages or costs relative to that of the same gender. $r_{w_m}^D r_{c_f}^D = 0$ if male and female labor are neither substitutes nor complements, and $r_{w_m}^D r_{c_f}^D > 0$ if they are either substitutes or complements. Given assumption 4 and substituting from equations 9, 11, 12 and 13, $r_{w_m}^D r_{c_f}^D < 1$. If male and female labor are neither substitutes nor complements, in which case $\delta = 1$, the equilibrium wage decreases whenever the demand elasticity in costs is larger than that of supply.

ONLINE APPENDIX

FOR ONLINE PUBLICATION ONLY

B Additional Theoretical Results

B.1 Prediction 6

We next evaluate how the equilibrium quantity and wage 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 can 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 and wages are increasing in gender-specific costs to substitute labor and decreasing in gender-specific costs to complement labor.*

Derivation We have shown in equations 12 and 13 that labor demand is increasing in gender-specific costs and wages to substitute labor and decreasing in gender-specific costs and wages to complement labor. We now evaluate how the equilibrium labor quantity and wages are changing in gender-specific costs. To evaluate the sign of $\frac{\partial L_m^*}{\partial c_f} = \frac{|J_2|}{|J|}$, we calculate $|J_2|$ and re-arrange:

$$|J_2| = \underbrace{\frac{\partial L_m^S}{\partial w_m}}_{>0} \left(\underbrace{\frac{\partial L_m^D}{\partial c_f}}_{?} \underbrace{\frac{\partial L_f^S}{\partial w_f}}_{+} - \underbrace{\frac{\partial L_m^D}{\partial w_f}}_{?} \underbrace{\frac{\partial L_f^S}{\partial c_f}}_{-} \right) \tag{20}$$

The above results from the fact that $\frac{\partial L_m^D}{\partial w_f}\frac{\partial L_f^D}{\partial c_f} - \frac{\partial L_m^D}{\partial c_f}\frac{\partial L_f^D}{\partial w_f} = 0$. The effect of an increase in costs to female labor depends on the substitutability of male and female labor. $\frac{\partial L_m^*}{\partial c_f} = 0$ iff male and female workers are neither substitutes nor complements, $\frac{\partial L_m^*}{\partial c_f} > 0$ iff they are substitutes and $\frac{\partial L_m^*}{\partial c_f} < 0$ iff they are complements. This is true for any $\alpha_f \in [0, 1]$. The results are equivalent for $\frac{\partial L_f^*}{\partial c_m}$.

Finally, to evaluate the sign of $\frac{\partial w_m^*}{\partial c_f} = \frac{|J_4|}{|J|}$, we calculate $|J_4|$ and re-arrange:

$$|J_4| = \underbrace{\frac{\partial L_m^D}{\partial c_f}}_{?} \underbrace{\frac{\partial L_f^S}{\partial w_f}}_{+} - \underbrace{\frac{\partial L_m^D}{\partial w_f}}_{?} \underbrace{\frac{\partial L_f^S}{\partial c_f}}_{-} \tag{21}$$

The above results from the fact that $\frac{\partial L_m^D}{\partial w_f}\frac{\partial L_f^D}{\partial c_f} - \frac{\partial L_m^D}{\partial c_f}\frac{\partial L_f^D}{\partial w_f} = 0$.

The effect of an increase in costs to female labor depends on the substitutability of male and female labor. $\frac{\partial w_m^*}{\partial c_f} = 0$ iff male and female workers are neither substitutes nor complements, $\frac{\partial w_m^*}{\partial c_f} > 0$ iff they are substitutes as the demand for male labor increases and $\frac{\partial w_m^*}{\partial c_f} < 0$ iff they are complements as the demand for male labor decreases. This is again true for any $\alpha_f \in [0, 1]$. The results are equivalent for $\frac{\partial w_f^*}{\partial c_m}$.

C Experiment Appendix

C.1 Information about Sample Industries

We recruit employers from Manufacturing, Retail & Services, and Education. According to the Bangladesh Bureau of Labour Statistics' 2016—2017 Labour Force Survey, urban workers in Retail & Services are 77% male, Manufacturing workers 61% male, and Education workers 53% male.[49] 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 versus 10,346 for women). Male Services & Retail workers earn about BDT 3800 more than women (USD 38; BDT 14,131 for men versus BDT 10,313 for women). In Education, men earn about BDT 3,200 more than women (USD 32; BDT 26,790 for men versus 23,568 for women; BBS (2018)).

[49] We calculate the Retail & Services employment rate combining wholesale and retail trade and repair of motor vehicles; accommodation and food service activities, activities of households as employers, and other service activities.

C.2 Night-Shift Workshop and Job

Figure C.1: Night-Shift Workshop and Job

C.3 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.

C.4 Random Wage Distribution in the Application Experiment

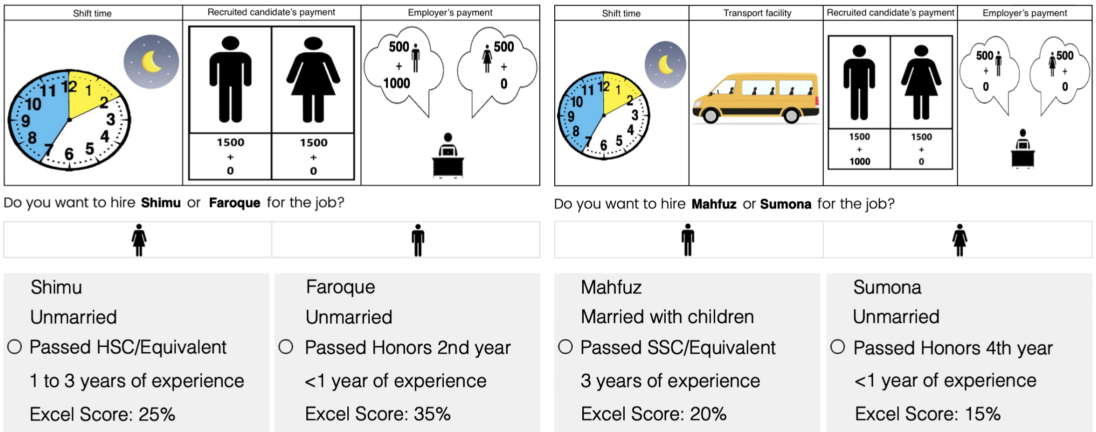
Table C.1: Random Wage Distribution in the Application Experiment

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

Notes: Table shows the wage distribution used to incentivize the reservation wage BDM in the application experiment.

C.5 Experimental Interfaces[50]

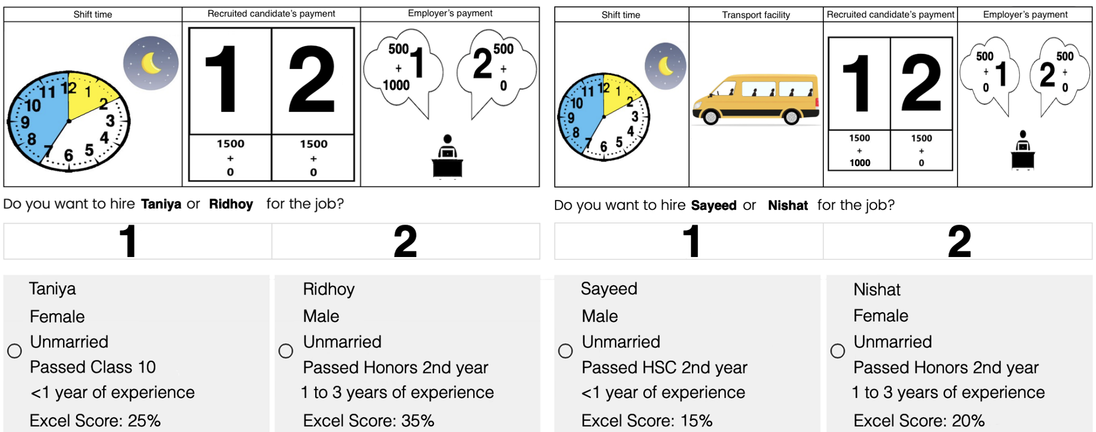
Figure C.2: Experimental Interface for Hiring Decisions



a) No Transport + Male Employer Subsidy

b) Transport + Male Worker Subsidy

Figure C.3: Low-Gender-Salience Experimental Interface for Hiring Decisions

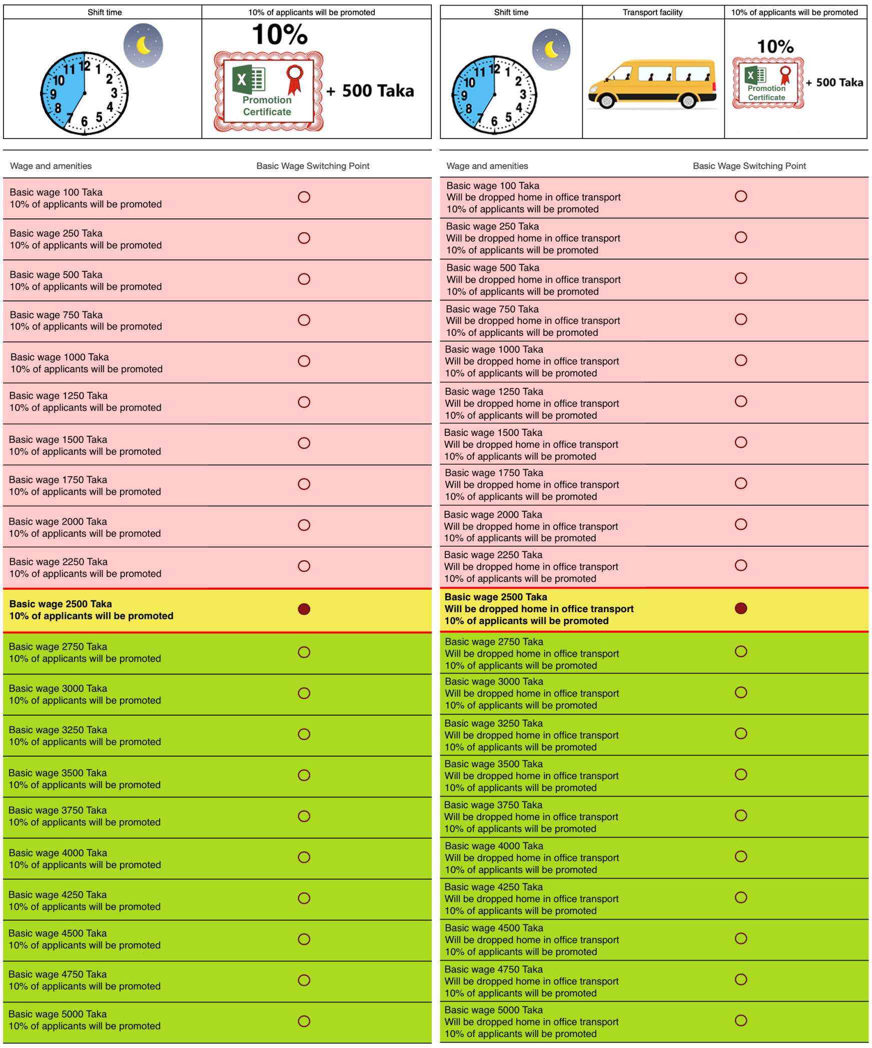


a) No Transport + Male Employer Subsidy

b) Transport + No Subsidy

[50] Translated from Bangla to English.

Figure C.4: Experimental Interface to Elicit Reservation Wage Decisions



a) No Transport b) Transport

D Structural Appendix

D.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. That is, we include the costs reported for the female worker and the compared male worker as well as their interactions with all subsidy treatments. 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. The coefficients on the male and female costs give us employers' reaction to male and female costs holding constant the costs of the other applicant. 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 $-1,000$. This gives us employers' evaluations of a one-Likert scale increase in terms of BDT paid to the worker.

D.2 Alternative Preference Estimation: Control Function

We test for robustness using a control function approach to address potential misreporting in welfare and profit predictions. We would like to estimate the following equation:

$$v_{ki} + \varepsilon_{ki} = d_j + \beta_j \Pi_{ki} + \alpha_{jg} \mathcal{W}_{ki} + \varepsilon_{ki}. \tag{22}$$

Assume we do not observe the true profit and welfare beliefs because of measurement error or misreporting. Instead, we observe $\Pi^*_{ki} = \Pi_{ki} + \varepsilon^{\Pi}_{ki}$ and $\mathcal{W}^*_{ki} = \mathcal{W}_{ki} + \varepsilon^{\mathcal{W}}_{ki}$ (for example, employers with high social image concerns might report low profits or welfare whenever they do not hire women to avoid appearing sexist). We can thus rewrite equation 22:

$$v_{ki} + \varepsilon_{ki} = d_j + \beta_j \Pi_{ki} + \alpha_{jg} \mathcal{W}_{ki} + \underbrace{\beta_j \varepsilon^{\Pi}_{ki} + \alpha_{jg} \varepsilon^{\mathcal{W}}_{ki}}_{\varepsilon^{end}_{ki}} + \varepsilon^{ex}_{ki}, \tag{23}$$

where ε^{end}_{ki} is potentially correlated with d_j, Π_{ki} and $\mathcal{W}_{ki}$ and ε^{ex}_{ki} is not correlated with d_j, $\mathcal{W}_{ki}$ nor Π_{ki}.

We adopt a two-step procedure similar to that developed by Rivers and Vuong (1988).[51]

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

First, let

$$\Pi_{ki} = Z_k'\kappa_j^{\Pi} + X_i'\gamma_j^{\Pi} + \tilde{\varepsilon}_{ki}^{\Pi} \tag{24}$$

and

$$\mathcal{W}_{ki} = Z_k'\kappa_j^{\mathcal{W}} + X_i'\gamma_j^{\mathcal{W}} + \tilde{\varepsilon}_{ki}^{\mathcal{W}}, \tag{25}$$

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, and Z_k constitutes a vector of transport and subsidy treatment assignments, which are independent of X_i, ε_{ki}^{Π}, $\varepsilon_{ki}^{\mathcal{W}}$, ε_{ki}^{end}, and ε_{ki}^{ex}. $\tilde{\varepsilon}_{ki}^{\mathcal{W}}$, $\tilde{\varepsilon}_{ki}^{\Pi}$, and ε_{ki}^{end} are jointly normal. We estimate equations 24 and 25 using OLS separately by industry (and across industries, including industry fixed effects).

Second, we plug the fitted residuals $\widehat{\tilde{\varepsilon}}_{ki}^{\Pi}$ and $\widehat{\tilde{\varepsilon}}_{ki}^{\mathcal{W}}$ (i.e., the endogenous parts of Π_{ki} and $\mathcal{W}_{ki}$ not explained by the random treatment assignments Z_k or applicant characteristics X_i) into equation 22 and estimate the following probit model:

$$v_{ki} + \varepsilon_{ki} = d_j + \beta_j\Pi_{ki} + \alpha_{jg}\mathcal{W}_{ki} + X_i\gamma + \delta^{\Pi}\widehat{\tilde{\varepsilon}}_{ki}^{\Pi} + \delta^{\mathcal{W}}\widehat{\tilde{\varepsilon}}_{ki}^{\mathcal{W}} + \tilde{\varepsilon}_{ki}^{ex}, \tag{26}$$

where $\tilde{\varepsilon}_{ki}^{ex}$, the error term after controlling for the fitted residuals (we also include industry fixed effects if we estimate equation 26 across industries), is i.i.d. normal with zero mean.

As expected, the employer subsidy increases the expected profit by approximately BDT 1,000 (USD 10) for female applicants but not male applicants in equation 24. By contrast, the *No Transport* treatment reduces the expected welfare by BDT 924 (USD 9) and BDT 1,700 (USD 17) for male and female applicants, respectively. The male and female worker subsidies increase the expected welfare of male and female workers by approximately BDT 1,000 (USD 10) each. Results from equation 26 suggest no mismeasurement in reported welfare or profits in the pooled sample ($p > 0.1$ for both $\widehat{\varepsilon^{\Pi}}$ and $\widehat{\varepsilon^{\mathcal{W}}}$, results not shown).

D.3 Beliefs Predictions: Random Forest Algorithm

We use a random forest algorithm to predict out-of-sample employer beliefs about profits and welfare based on treatment assignment, employer characteristics, and applicant characteristics. To determine the number of variables to consider in each tree and the number of trees to estimate, we use a grid search and select the combination of parameters that creates the lowest mean out-of-sample error.

The main predictors of productivity are 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 transport, applicant gender, the employer's industry, and how many hiring choices the employer made in the last three years.

D.4 Simulating Labor Demand: CES Production Function

The production function of employers in industry j is:

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

where p is the piece rate, $\widehat{Y}_{jf}$ and $\widehat{Y}_{jm}$ are the employer's beliefs about 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. We assume that employers have degenerate, point-beliefs. This assumption implies that the expected value of a function, $E[f(x)]$, equals the function of the expected value, $f(E[x])$, which allows us to derive the results in this section. The employer's utility from profits is β_j (we use this notation to match our structural analysis, in monetary terms $\beta_j = 1$). 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:

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

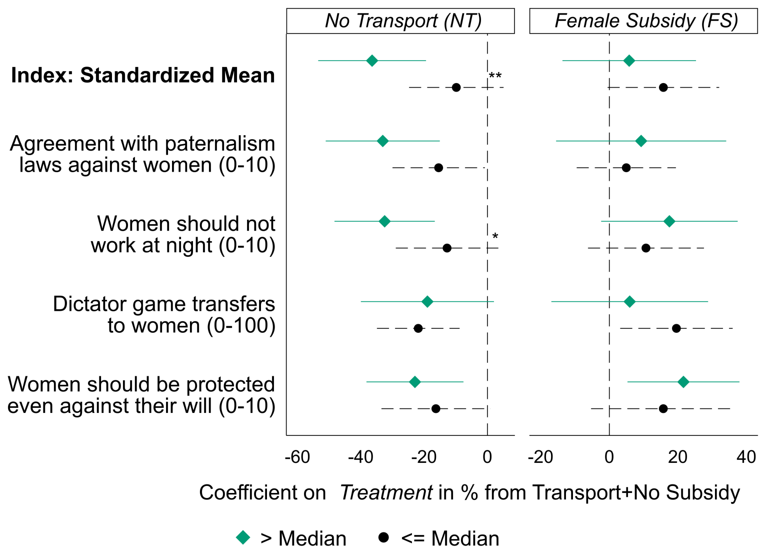
Rearranging, we can solve for the labor g demand:

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

We simulate labor demand using a symmetric CES function, $a_{jf} = a_{jm} = \frac{1}{2}$, a substitution parameter of $\rho = 0.8$ (i.e., male and female workers are substitutes as in the experiment, results are qualitatively the same when using $\rho = 0.7$ or $\rho = 0.9$). We calibrate the returns-to-scale parameter υ such that the equilibrium wage for male workers with transport is BDT 1,500 (USD 15) as in the experiment (this results in $\upsilon \approx 0.896$). We calibrate the piece rate p paid to employers for each task to match the average payoffs in the experiment, resulting in BDT 124 (USD 1).

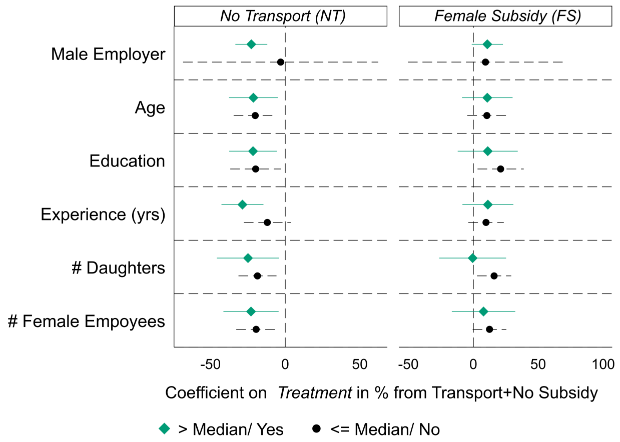
E Empirical Appendix

Figure E.1: Treatment Effects on Hiring by Other-Regarding Preferences



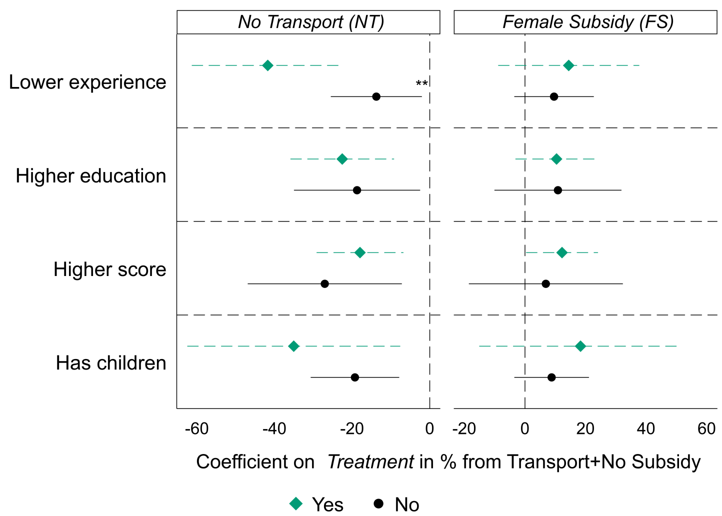
Notes: The graph shows the coefficients on the *No Transport* and *Female Subsidy* indicators from regression 3, respectively. Regressions are run separately among different subsets of employers (see section 4.2). That is, each coefficient shows how much employers in that group reduce female hiring when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

Figure E.2: Treatment Effects on Hiring by Employer Characteristics



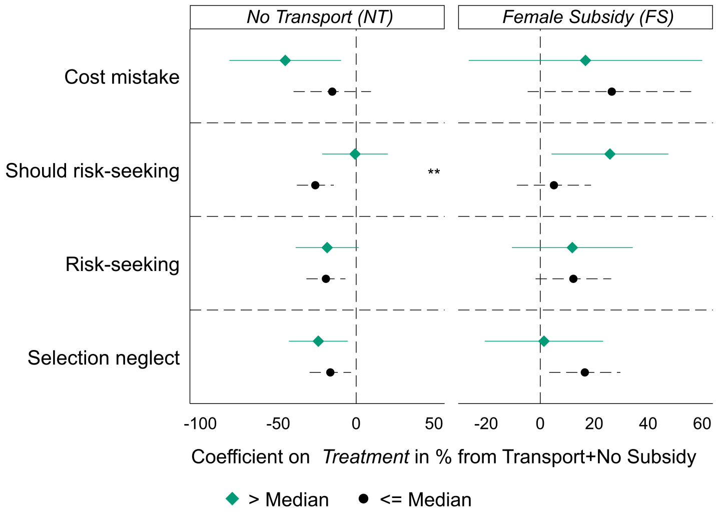
Notes: The graphs show the coefficients on the *No Transport* and the *Female Subsidy* indicators from regression 3 run separately within different employer subsamples. We do not include applicant fixed effects for insufficient observations and instead control for all characteristics of both applicants shown to the employer. We compare female versus male employers, employers who made up to seven hiring choices in the last three years (the median) versus employers who made more than seven hiring choices, employers age 30 or younger (the median) with employers that are older than 30, employers with a high school degree or less (the median) with employers with more than a high school degree, employers with or without daughters and with or without female employees. Asterisks indicate significantly different coefficients between subsamples. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Figure E.3: Hiring by Treatment Assignment and Applicant Characteristics



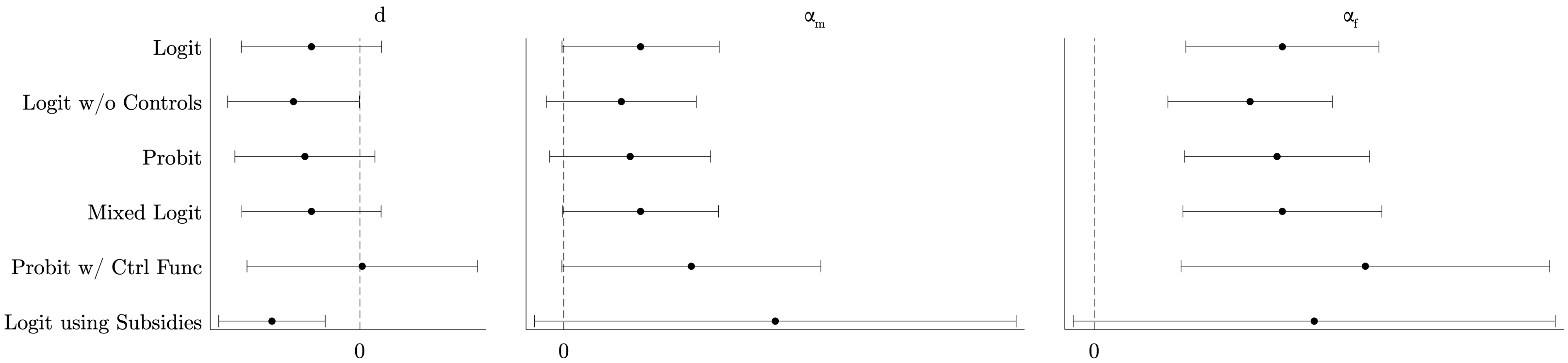
Notes: The graphs show the coefficients on the *No Transport* and the *Female Subsidy* indicators from regression 3 run separately within different pairs. We do not include applicant fixed effects for insufficient observations and instead control for all characteristics of both applicants shown to the employer. 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 indicate significantly different coefficients between subsamples. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Figure E.4: Hiring by Treatment Assignment and Employer Characteristics



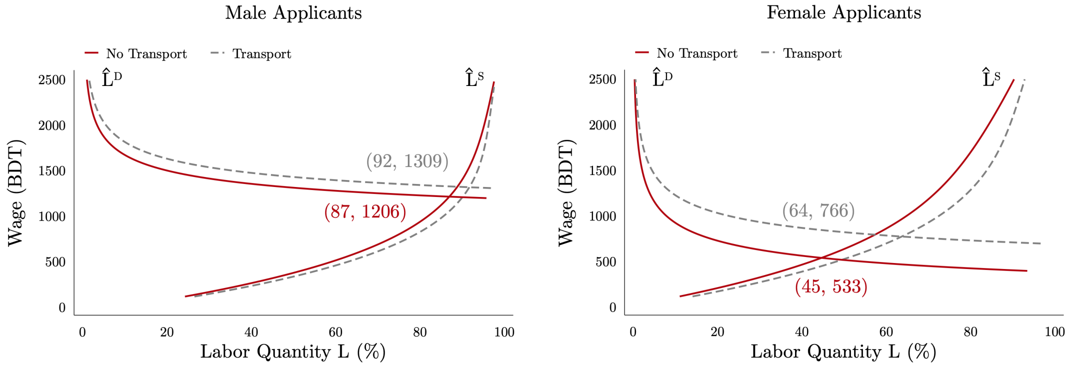
Notes: The graphs show the coefficient estimates and 95% confidence intervals for *No Transport* and the *Female Subsidy*. We run the regressions in different subsets of employers (see section 4.2). We do not include applicant fixed effects for insufficient observations and instead control for all characteristics of both applicants shown to the employer. Asterisks indicate significantly different coefficients between subsamples. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Figure E.5: Parameter Robustness



Notes: The graph shows the estimated coefficients and 95% confidence intervals of the preference parameters for a series of specifications. (i) "Logit" estimates equation 5 controlling for a vector of applicant characteristics (Excel screening score, education, work experience, and marriage status). (ii) "Logit without Controls" estimates the same specification without controls. (iii) "Probit" estimates the same specification using probit instead of logit regression. (iv) "Mixed Logit" estimates heterogeneous preferences using mixed logit that takes advantage that we have four observations per employer. (v) "Probit with Control Function" employs a control function approach to address potential endogeneity concerns of the reported productivity and cost beliefs (see also section D.2). (vi) "Logit using Subsidies" estimates α_m and α_f on only the exogenously varied wages paid by employers or received by workers. The confidence intervals are based on bootstrapped standard errors. Standard errors are based on 1,500 bootstrap samples clustered at the employer level. We retain only those bootstrap samples where the estimation routine converged within 50 iterations, resulting in 1,500, 1,500, 1,499, 1,082, 1,500, 1,500 bootstrap samples for the 6 datasets, respectively.

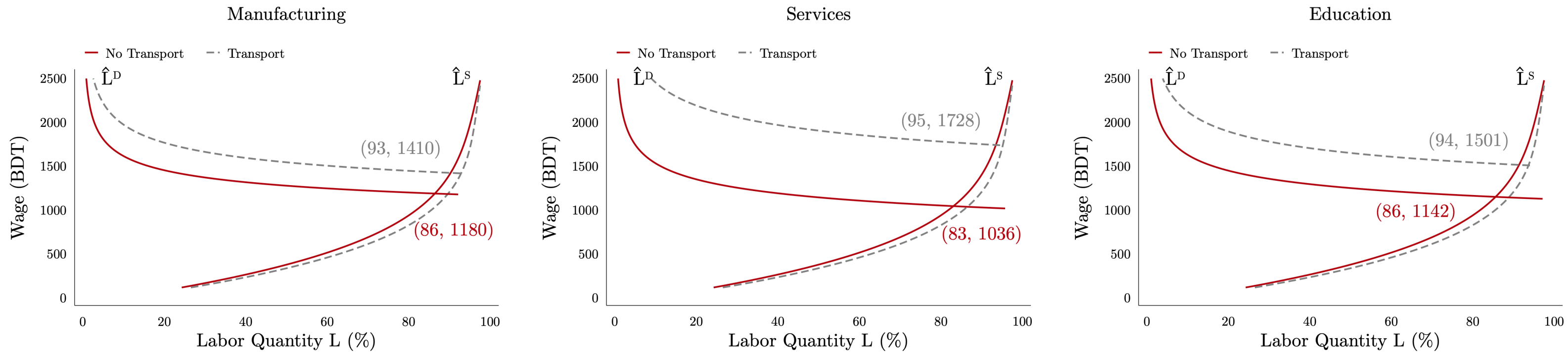
Figure E.6: Equilibria in the Male and Female Labor Markets
Holding Selection and Productivity Constant Across Wages and Transport Conditions



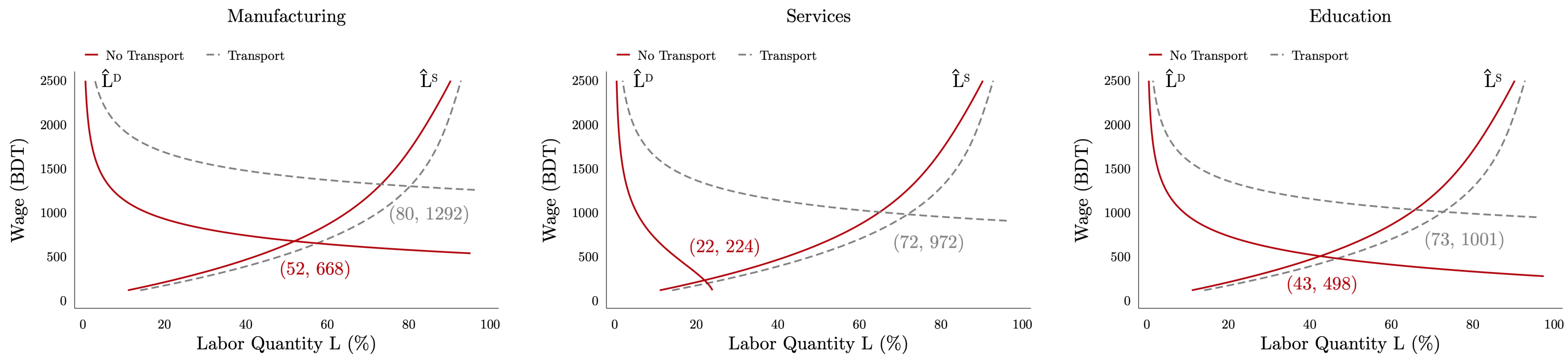
Notes: The graph shows the share of workers demanded and supplied in male and female labor markets at each wage with and without transport. We use predicted productivity and cost beliefs from the *Beliefs-Elicitation* employers (see section 6.1.3) and calculate profits using the CES production function described in appendix D.4. Numbers in parentheses in the graph give (L_g^*, w_g^*). Numbers in gray on top are the equilibrium with transport and numbers in red in the bottom are the equilibrium without transport.

Figure E.7: Equilibria in the Male and Female Labor Markets

(E.7.1) Market for Male Workers



(E.7.2) Market for Female Workers



Notes: The graph shows the share of workers demanded and supplied in male and female labor markets at each wage 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 the CES production function described in appendix D.4. Numbers in parentheses in the graph give (L_g^*, w_g^*). Numbers in gray on top are the equilibrium with transport and numbers in red in the bottom are the equilibrium without transport.

Table E.1: 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**		**Transport**
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 (%)	82.37	25.72	80.88	24.23	65.66	9.01	73.38	16.73	67.23	-39.38	74.28	-17.11	58.29	-40.82	56.65
	(38.11)	(0.00)	(39.35)	(0.00)	(47.51)	(0.30)	(44.22)	(0.03)	(46.97)	(0.00)	(43.73)	(0.13)	(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 in each treatment). **No Transport (NT)** includes all employers in the *No Transport+No Subsidy* treatment; **Male Subsidy (MS)** includes all employers in the *Transport+Male Subsidy* treatment; **Female Subsidy (FS)** includes all employers in the *Transport+Female Subsidy* treatment; **Employer Subsidy (ES)** includes all employers in the *Transport+Employer Subsidy* treatment. "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** indicates the joint significance of all variables in predicting treatment assignment (excluding "Education (%)", which is perfectly collinear with "Manufacturing (%)" and "Retail & Services (%)").

Table E.2: Employer 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**		**Transport**
	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	990		349		463		586		384		466		355		928
Productivity (P(Show-up) $\times$ E[Tasks|Show-up])	39.65	0.98	39.75	1.09	34.78	-3.88	38.05	-0.62	47.46	6.72	41.41	5.64	35.30	-3.73	38.67
	(21.17)	(0.70)	(21.04)	(0.76)	(18.56)	(0.19)	(21.32)	(0.84)	(22.25)	(0.18)	(21.95)	(0.20)	(19.69)	(0.40)	(20.17)
Predicted Revenue (BDT)	697.76	2.96	701.14	6.35	674.18	-20.61	690.32	-4.47	736.73	32.63	707.04	29.89	675.97	-17.32	694.80
	(106.25)	(0.82)	(106.36)	(0.73)	(93.26)	(0.17)	(107.07)	(0.77)	(111.87)	(0.20)	(109.75)	(0.18)	(97.49)	(0.44)	(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)
Perceived Costs (0–10)	2.50	1.63	1.08	0.22	0.64	-0.22	0.72	-0.14	1.89	-0.82	2.16	-0.11	1.83	-0.52	0.87
	(2.18)	(0.00)	(1.10)	(0.29)	(1.25)	(0.24)	(1.21)	(0.43)	(1.82)	(0.04)	(1.87)	(0.78)	(2.04)	(0.22)	(1.20)
Perceived Costs (BDT)	1399.77	924.39	598.07	122.69	361.56	-113.82	406.43	-68.95	1048.39	-474.07	1206.23	-79.72	1050.66	-280.16	475.38
	(1215.21)	(0.00)	(614.75)	(0.29)	(702.31)	(0.29)	(678.73)	(0.49)	(1016.59)	(0.04)	(1040.09)	(0.71)	(1141.80)	(0.24)	(670.38)
Female Applicants: N	990		352		466		586		385		467		357		929
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)	588.47	5.48	583.50	0.51	587.25	4.25	593.32	10.33	588.73	-0.25	586.40	-6.32	591.10	-7.69	582.99
	(28.26)	(0.10)	(30.40)	(0.91)	(30.82)	(0.32)	(26.43)	(0.01)	(28.25)	(0.97)	(29.26)	(0.31)	(27.64)	(0.15)	(29.46)
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)	3507.20	1702.56	2476.51	671.87	1669.29	-135.35	1702.30	-102.34	3345.81	-833.26	3248.83	-123.01	2860.52	-544.34	1804.64
	(1400.40)	(0.00)	(1127.82)	(0.00)	(1222.39)	(0.50)	(1217.97)	(0.60)	(1205.95)	(0.01)	(1284.91)	(0.68)	(1629.86)	(0.12)	(1225.17)

Notes: The table shows employers' beliefs about applicant characteristics by treatment arm of all applicants in the hiring experiment. N indicates observations of employer–applicant pairs. **No Transport (NT)** includes all employers in the *No Transport+No Subsidy* treatment; **Male Subsidy (MS)** includes all employers in the *Transport+Male Subsidy* treatment; **Female Subsidy (FS)** includes all employers in the *Transport+Female Subsidy* treatment; **Employer Subsidy (ES)** includes all employers in the *Transport+Employer Subsidy* treatment. $\beta_{[treatment]}$ indicates the coefficient estimates from a regression of the variable on an indicator for treatment status with modified Huber–White robust SEs. *Productivity* indicates employers' beliefs about the number of tasks (out of 100) that an applicant will complete conditional on showing up for the shift. *Predicted Revenue* indicates employers expected payoff from hiring a given applicant. *Actual Revenue* indicates the realized payoffs to employers from hired workers. *Perceived Costs (0–10)* indicates employers' beliefs about applicants' on-the-job costs on a 0–10 Likert scale. *Perceived Costs (BDT)* indicates employers' beliefs about on-the-job costs converted to money.

Table E.3: Productivity and Cost Predictions, *Hiring* and *Prediction-Only* Employers

	Employer Type		
	Hiring		*Prediction-Only*
	Mean (SD)	β_{Pred} (p-val)	Mean (SD)
Male Applicants: *N*	1,408		319
Productivity (P(Show-up) $\times$ E[Tasks|Show-up])	41.54	-3.85	37.69
	(21.93)	(0.11)	(21.21)
Perceived Costs (0–10)	2.28	0.15	2.43
	(2.06)	(0.59)	(2.22)
Female Applicants: *N*	1,406		320
Productivity (P(Show-up) $\times$ E[Tasks|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: Table shows predictions of the *Hiring* and *Prediction-Only* employers recruited simultaneously. We exclude employers *Hiring* employers recruited before *Prediction-Only* recruitment began. N indicates the number of employer–applicant pairs. β_{Pred} shows the coefficient and p-values from an OLS regression of each variable on an indicator that is 1 for *Prediction-Only* employers (modified Huber–White standard errors not shown).

Table E.4: Treatment Effects on Hiring, Robustness Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
No transport (NT)	-9.729***	-9.653***	-9.729***	-9.189***	-9.377***	-9.943***	-11.528***	-9.774***	-9.729***	-0.617***	-34.902***
	(2.486)	(2.444)	(2.487)	(2.465)	(2.443)	(2.469)	(3.548)	(2.590)	(2.630)	(0.150)	(6.021)
Male subsidy (MS)	-7.263**	-6.899**	-7.263**	-6.230*	-6.848**	-6.869**	-9.104**	-7.104**	-7.263**	-0.459**	
	(3.256)	(3.264)	(3.259)	(3.261)	(3.059)	(3.224)	(4.146)	(3.251)	(3.487)	(0.191)	
Female subsidy (FS)	7.203***	4.843*	7.203***	4.859*	7.685***	7.714***	8.285**	6.787**	7.203**	0.433***	
	(2.765)	(2.667)	(2.767)	(2.702)	(2.739)	(2.806)	(3.678)	(2.857)	(2.949)	(0.159)	
Employer subsidy (ES)	22.931***	22.729***	22.931***	22.855***	22.807***	23.100***	22.974***	22.330***	22.931***	1.385***	
	(3.122)	(3.063)	(3.124)	(3.089)	(3.084)	(3.138)	(4.347)	(3.223)	(3.297)	(0.191)	
NT*MS	0.851	-0.963	0.851	-1.126	0.968	0.876	3.093	1.414	0.851	0.054	
	(4.401)	(4.300)	(4.404)	(4.351)	(4.301)	(4.384)	(5.997)	(4.564)	(4.702)	(0.269)	
NT*FS	-4.969	-3.850	-4.969	-4.486	-6.894*	-4.996	-7.385	-4.923	-4.969	-0.271	
	(4.079)	(4.007)	(4.082)	(4.008)	(3.908)	(4.099)	(5.779)	(4.147)	(4.276)	(0.238)	
NT*ES	0.666	-0.335	0.666	-0.814	0.458	1.514	0.835	1.228	0.666	0.036	
	(5.339)	(5.268)	(5.343)	(5.307)	(5.119)	(5.372)	(7.800)	(5.441)	(5.553)	(0.308)	
Applicant: Excel score		1.338***		1.313***							
		(0.060)		(0.059)							
Applicant: Education		2.250***		1.832***							
		(0.310)		(0.303)							
Applicant: ≤ 3 yrs work experience		-10.727***									
		(2.334)									
Applicant: Married		-5.586***									
		(2.069)									
Applicant: Has children		-1.714									
		(2.805)									
Control Mean	45.318	45.269	45.269	45.318	45.971	45.158	48.092	45.998	45.318	45.318	55.000
Observations	4532	4539	4539	4532	4815	4482	2570	4080	4532	4173	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 1). 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 (for whom spillovers are impossible). 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) due to small sample size). $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Table E.5: Applicant Characteristics in the Application Experiment

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

Table E.6: 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)	(15)	(16)
No transport (NT)	167.516*	-0.044	140.286*	217.414	179.465**	203.575**	105.113*	176.543**	239.841*	-0.130*	246.949*	215.525	238.095*	221.388	-16.016	162.023
	(92.523)	(0.048)	(76.212)	(146.505)	(88.303)	(89.773)	(59.888)	(85.941)	(141.490)	(0.069)	(128.997)	(173.132)	(137.016)	(136.263)	(64.003)	(135.064)
Control Mean	478.297	0.934	408.333	552.473	478.297	478.297	370.882	474.623	802.663	0.858	735.671	848.521	802.663	802.663	521.724	810.677
Observations	352	352	335	352	352	352	326	389	344	344	333	344	344	344	279	379
Main	✓								✓							
Applied		✓								✓						
Truncating			✓								✓					
Keep outliers				✓								✓				
No controls					✓								✓			
Post-Double-Selection						✓								✓		
Reservation wage $\leq 1,500$							✓								✓	
Understanding								✓								✓

Notes: The table shows results from OLS regressions with Huber–White robust SEs (see equation 4 and notes to figure 3). 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 only keep applicants with a reservation wage of $\leq$ BDT 1,500 in columns (7) and (15) and include applicants with incorrect understanding questions in columns (8) and (16). $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Table E.7: Employer Preference Parameter Estimates, Mixed Logit

	Pooled		Manufacturing		Services		Education	
	μ	σ	μ	σ	μ	σ	μ	σ
d	-0.115	0.000	-0.024	0.000	-0.073	0.000	-0.201	0.000
	(0.084)	(0.047)	(0.137)	(0.075)	(0.432)	(0.044)	(0.114)	(0.050)
α_m	0.111*	0.000	0.011	0.000	0.261	0.000	0.121	0.000
	(0.057)	(0.019)	(0.093)	(0.099)	(3.018)	(0.091)	(0.084)	(0.013)
α_f	0.174***	0.005	0.175***	0.000	0.257	0.117	0.155**	0.182
	(0.047)	(0.078)	(0.067)	(0.028)	(4.248)	(2.198)	(0.076)	(0.117)
p-val ($\alpha_m = \alpha_f$)	0.396	.	0.153	.	0.999	.	0.763	.
Observations	1,816	.	606	.	588	.	622	.

Notes: The table presents parameter estimates from a mixed logit model, estimated among mixed-gender hiring pairs, assuming normally distributed random parameters. We control for the applicant characteristics shown to employers, including Excel screening score, education, work experience, and marital status. All estimates in money metric. d in '000 BDT. Standard errors are based on 1,500 bootstrap samples clustered at the employer level. Standard errors are calculated using 1,500 bootstrap samples clustered at the employer level. We retain only those bootstrap samples where the estimation routine converged within 50 iterations, resulting in 1,082, 1,223, 1,177, and 1,290 samples for the pooled data and the three industry-specific datasets, respectively. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Table E.8: Employer Preferences: Heterogeneity by Other-Regarding Index

	$\leq$ Median	$>$ Median
d	-0.226	-0.058
	(0.125)	(0.141)
α_m	0.022	0.180
	(0.083)	(0.113)
α_f	0.064	0.268***
	(0.061)	(0.104)
p-val ($\alpha_m = \alpha_f$)	0.682	0.564
Observations	910	906

Notes: The table presents parameter estimates from a logit model, estimated among mixed-gender hiring pairs. We control for the applicant characteristics shown to employers, including Excel screening score, education, work experience, and marital status. We divided the sample by the median other-regarding index used to test prediction 4. All estimates in money metric. d in '000 BDT. Standard errors are based on 1,500 bootstrap samples clustered at the employer level. We retain only those bootstrap samples where the estimation routine converged within 50 iterations, resulting in 1,496 and 1,499 bootstrap samples for the below and above median datasets, respectively. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Table E.9: Employer Characteristics, by Industry

	Manufacturing		Services		Education	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Female (%)	3.9	19.5	1.3	11.5	13.3	34.1
Age (Years)	32.4	7.8	32.2	7.8	29.9	7.7
Married (%)	72.5	44.8	62.4	48.6	41.1	49.4
Children (%)	58.2	49.5	49.7	50.2	28.5	45.3
Bachelor's (%)	11.8	32.4	32.0	46.8	81.0	39.3
# Male Employees	11.0	37.6	3.2	4.0	12.4	17.0
# Female Employees	11.5	71.0	0.2	0.9	6.3	9.6
# Hiring Decisions Last 3 Years	53.2	405.3	10.3	25.5	17.8	37.1

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 equal to 1 if the applicant has at least one child. *Bachelor's* is an indicator equal to 1 if the applicant has at least a Bachelor's degree.

Table E.10: Treatment Effect on Intensive and Extensive Margin

	Hired Woman (%)	# Women
	(1)	(2)
No transport (NT)	-0.017	-0.920***
	(0.024)	(0.236)
Male subsidy (MS)	-0.033	-0.619**
	(0.041)	(0.286)
Female subsidy (FS)	0.001	0.531**
	(0.026)	(0.247)
Employer subsidy (ES)	0.022	1.974***
	(0.015)	(0.300)
NT*MS	-0.003	0.030
	(0.063)	(0.409)
NT*FS	0.015	-0.343
	(0.039)	(0.389)
NT*ES	-0.012	0.374
	(0.037)	(0.510)
Control Mean	0.979	4.587
Observations	460	446

Notes: The table shows results from OLS regressions with Huber–White robust SEs, controlling for 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. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Table E.11: Counterfactuals: Benchmarking the Effect 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^* (%)	86	86	86	86	86	86	86	87	89
L_f^* (%)	44	64	63	54	51	53	55	50	69
$L_m^* - L_f^*$ (ppts)	42	22	23	31	35	33	30	37	20
w_m^* (BDT)	1146	1166	1165	1157	1154	1163	1157	1200	1304
w_f^* (BDT)	516	967	931	720	646	692	442	621	1137
$w_m^* - w_f^*$ (BDT)	631	200	234	437	508	471	715	579	167
$\mathcal{W}_m^E$ ('000 BDT)	-122	-115	-115	-118	-119	-116	-118	50	371
$\mathcal{W}_m^A$ ('000 BDT)	308	316	315	312	311	315	312	329	371
$\mathcal{W}_f^E$ ('000 BDT)	-614	-739	-736	-699	-675	-691	-808	-547	216
$\mathcal{W}_f^A$ ('000 BDT)	46	161	150	91	73	84	47	67	216
Π ('000 BDT)	2157	2305	2298	2247	2220	2237	2415	2209	2319

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 E.12: Effects of Counterfactual Transport and Subsidy Interventions

	Status Quo	**Transport**	**Subsidies**
L_m^* (%)	86	87	86
L_f^* (%)	44	75	76
$L_m^* - L_f^*$ (ppts)	42	12	11
w_m^* (BDT)	1146	1186	1176
w_f^* (BDT)	516	1067	1434
$w_m^* - w_f^*$ (BDT)	631	120	-258
$\mathcal{W}_m^E$ ('000 BDT)	-122	-107	-111
$\mathcal{W}_m^A$ ('000 BDT)	308	324	320
$\mathcal{W}_f^E$ ('000 BDT)	-614	-246	-708
$\mathcal{W}_f^A$ ('000 BDT)	46	219	317
Π ('000 BDT)	1975	2590	2205
Gov't Cost ('000 BDT)	0	269	269

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 and 2) a BDT 900 subsidy for hiring female workers paid to 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 government (in '000 BDT).