

Paternalistic Discrimination*

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We combine two field experiments in Bangladesh with a structural labor model to 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. We observe real hiring and application decisions for a night-shift job that provides safe worker transport home at the end of the shift. In the first experiment, we vary employers’ perceptions of job costs to female workers by experimentally varying information about the transport but holding taste-based and statistical discrimination constant. Not informing employers about the transport decreases demand for female labor by 22%. Employers respond more to transportation information than to a cash payment to female workers that would allow them to purchase safe transport for themselves. This suggests that employers paternalistically prevent women from making their own choices. In the second experiment, not informing applicants about the transport reduces female labor supply by 15%. In structural simulations that combine the results of both experiments, eliminating paternalistic discrimination reduces the gender employment gap by 24% and increases female wages by 21%.

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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 protect women (Glick et al., 2000), this discrimination might be particularly prevalent against women. Governments around the world restrict women's employment in jobs perceived as dangerous: 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 workers' 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 their workers' welfare and thus hire fewer workers with low perceived welfare. Building on traditional models of discrimination, our model incorporates a simple distaste for one particular gender (taste-based discrimination), beliefs about the profitability of hiring from a particular gender (statistical discrimination), and beliefs about the welfare of a particular gender (other-regarding discrimination).

¹ Outside of the labor market, parents may be more protective of their daughters than their sons (Bezirgianian and Cohen, 1992; Kuhle et al., 2015). In addition, women may receive different advice from teachers or advisors about educational tracks, 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 limit women's employment in Argentina, Cameroon, China, the Republic of Korea, Saudi Arabia, and other countries (US Department of State, 2022b,c; World Bank, 2023b). In South Asia, such laws are prevalent: Women in India face different restrictions than men when working at night, performing hazardous or difficult tasks (such as lifting heavy objects), and selling alcohol (Anand and Kaur, 2022). In addition, all but 17 countries ban women from fighting in combat (Fitriani et al., 2016).

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 22% 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 selection, 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 woman compared to the same man. 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 In addition, to ensure that differences in hiring are not explained by concerns about the employers' reputation, all hiring choices are private and anonymous. We limit our sample to employers who correctly respond to all comprehension checks and understand that the transport neither influences selection nor productivity. We also verify using survey questions that employers do not differentially base their hiring choices on taste, statistical, or reputation concerns across treatment arms.

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. They thus demand workers weakly more when workers receive sufficient cash to decide themselves whether to purchase safe transport, rather than when workers receive the transport itself. Paternalistic employers, on the other hand, may demand workers less with the 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: (i) female workers receive a surprise payment of 1,000 Bangladesh Taka (BDT, or USD 10)—an amount much

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

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 payment of BDT 1,000, (iii) employers receive a payment for hiring female workers of BDT 1,000, or (iv) neither employers nor workers receive a payment. We find that employers hire women significantly less with the female worker payment than with the transport—even though rational 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 payments.

We test whether employers who score highly in a survey module on other-regarding preferences towards women react more to information about the transport to test the fourth theoretical prediction: The demand response to changes in perceived worker welfare increases in employers' other-regarding preferences (deferential or paternalistic). We find that *more* other-regarding employers react almost four times as much to the transport than *less* other-regarding employers. This difference suggests that our findings indeed reflect other-regarding preferences rather than, for example, experimenter demand effects, i.e., employers trying to satisfy the experimenters' preferences.⁴

Employers' response to information about the transport and female worker subsidies appears to be driven by employers disagreeing with both applicants' *beliefs* about 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.⁵ Overall, these heterogeneous treatment effects offer additional evidence that (male) employers are paternalistic rather than deferential.

To evaluate the market's equilibrium behavior, 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 hiring experiment, increase by BDT 200 (USD 2), which is much less than employers' valuation of female worker transport of BDT 1,400 (USD 14, calculated from employers' hiring responses to the transport

⁴ In addition, while experimenter demand effects should *decrease* when making the study purpose less salient, we find that treatment effects *increase* in a small “low-salience” control test.

⁵ However, we consider these results as suggestive given our small sample of female employers.

and female worker subsidies).

We estimate the model parameters and combine the results of the demand- and supply-side experiments to study the fifth theoretical prediction: Equilibrium wages decrease in perceived job costs if the labor demand decreases more than the labor supply. We construct the labor demand function by estimating preference parameters in a binary choice model using the hiring choices in the hiring experiment. We construct the labor supply function by aggregating the reservation wages in the application experiment. We combine the two functions to construct equilibria for both genders with and without transport in the market for our night-shift job. We find that without transport, equilibrium labor quantities decrease by 15% for women and 7% for men, while wages decrease by 19% for women and 12% for men. We present results from two sets of counterfactuals. First, eliminating paternalistic discrimination reduces the gender employment gap by 24% and increases female wages by 21%. Paternalistic discrimination appears to be as important as statistical discrimination and more important than taste-based discrimination in our experimental setting. Second, the cost-effectiveness of transport and subsidy interventions depends on the accuracy of beliefs about job costs for workers: Transport increases total welfare more if employers have correct beliefs while female subsidies increase total welfare more if applicants have correct beliefs.

While we demonstrate that paternalistic discrimination may reduce female and employment and wages, the welfare effects are ambiguous. If employers are well-informed about the dangers on the job, paternalism may help women avoid pitfalls; on the other hand, if women understand the risks, paternalism may restrict them from accessing beneficial opportunities.

The extent of paternalism revealed in our experiment suggests opportunities for increasing female employment and wages in settings with strong gender norms. While we model other-regarding employers, our model is observationally equivalent to one in which employers *act as if* they internalize workers' welfare. For example, employers may follow a protective social norm (Boudet, 2013; Jayachandran, 2021) or signal their identity as a protective person (Akerlof and Kranton, 2000).⁶ However, policies that reduce paternalistic discrimination may also eliminate some self-regarding reasons to discriminate, by changing norms or eliminating socially-acceptable covers for taste-based discrimination. While previous research has shown that addressing work-related danger and unsafe transportation can increase the *supply* of female labor (Field and Vyborny, 2022; Cheema et al., 2022), our findings suggest that these policies can also increase the *demand* for female labor. This implies that there are compounding benefits from policies that reduce women's perceived job costs (e.g., crime reduction programs and workplace safety regulation) or increase their perceived benefits (e.g., wage laws and subsidies).

We contribute to three separate strands of literature. First, we contribute to the literature on

⁶ 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 payment. This behavior appears more consistent with our model of other-regarding preferences.

discrimination by defining a novel form of discrimination. A large body of literature measures taste-based and statistical discrimination on a variety of characteristics (see, among others, [Goldin, Claudia, and Cecilia 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](#)). Paternalistic discrimination differs from taste-based discrimination, as it varies with workers’ perceived welfare.⁷ It also differs from statistical discrimination in two key ways. First, it is driven by other-regarding rather than self-regarding motives—indeed, employers are willing to forego profits to indulge their paternalism. Second, unlike statistical discrimination, it does not require any uncertainty, as paternalistic employers may overrule applicants’ preferences even if job costs are known with certainty. We consider paternalistic discrimination to be most closely related to 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](#)). This paper draws on the benevolent sexism literature to formalize the first economic model of paternalistic discrimination.⁸

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](#)). Researchers have also explored the drivers of and responses to paternalism ([Uhl, 2011](#); [Ambuehl et al., 2021](#); [Bartling et al., 2023](#)), and the relationship between paternalism and altruism ([Jacobsson et al., 2007](#)). Most relevant to our setting, other-regarding preferences also drive behavior in the workplace, including wage setting ([Akerlof, 1982](#)), workers’ effort ([Asad et al., 2023](#); [Bandiera et al., 2005](#)), resource allocation ([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 barriers to female labor force participation, particularly in low-income countries. Among other factors, this literature considers social

⁷ Our experimental evidence cannot be explained by a distaste parameter that is constant across jobs, so we reject the simplest formulation of the traditional model. As a result, we describe paternalistic discrimination as a novel form of discrimination. The alternative interpretation—that paternalistic discrimination is a component of taste-based discrimination that varies with job characteristics—is equally valid. Paternalistic discrimination could also both result from and induce systemic discrimination ([Bohren et al., 2022](#)). Paternalistic discrimination may 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 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*, which generally refers to discriminatory policies designed to benefit minority or marginalized groups (see, for example, [Evans 1974](#) and [Patty 1989](#)).

norms (e.g., Fernández, 2013; Bertrand et al., 2015; Bernhardt et al., 2018, 2019; Bursztyn et al., 2020; Field et al., 2021; McKelway, 2023; see Jayachandran, 2021 for an overview) and safety (Chaudhary et al., 2021; Field and Vyborny, 2022; Siddique, 2022; Becerra and Guerra, 2023) as barriers to female labor supply. 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 paternalistic employers restrict women’s employment, particularly in South Asia.

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

2 A Labor Market Model with Other-Regarding Employers

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

2.1 Setup

Market Structure We study two markets, one for each gender $g \in \{m, f\}$.⁹ A unit mass of price-taking employers, indexed by k , demand labor in the two markets. A unit mass of male ($g = m$) and a unit mass of female ($g = f$) price-taking workers, indexed by i , supply labor. We use the superscripts A and E to denote preferences and beliefs of workers (i.e., applicants) and employers, respectively. The mass of gender g workers supplying labor is given by L_g^S , and the mass of gender g workers demanded by employers is given by L_g^D . Wages for gender g labor and the quantity of hired gender g labor are determined in equilibrium. w_m^* and w_f^* are the equilibrium wages that equate the labor supply and labor demand for both genders simultaneously. L_m^* and L_f^* are the equilibrium quantities of both genders at these wages.

⁹ The setup generalizes to more groups, each having a separate market.

Workers' Problem Workers supply their labor if their expected utility from working is weakly positive.¹⁰ Worker i 's expected money-metric utility from working for employer k depends on the wage w_g , the expected costs c_{igk} , and the disutility associated with the cost of working $u_i^A(\cdot)$, where u_i^A is continuously differentiable and monotonically increasing in c_{igk} , with $u_i^A(0) = 0$.¹¹ The cost of worker i of gender g working for employer k (including opportunity costs) is given by $c_{igk} = c_g + c_i + c_{kg}$, 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.¹² We assume that applications are costless such that applicant i of gender g supplies labor if and only if:

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

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} male workers at wages w_f and w_m , and (iii) fraction $\alpha_{kg} \in (0, 1)$ of the expected on-the-job welfare of the worker, as perceived by employer k , \mathcal{W}_{kg} (henceforth "welfare").¹³ 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.¹⁴ Employers understand selection, realizing that the pool of applicants consists only of workers who believe the job will yield positive utility, i.e., for whom $\mathcal{W}_{kg}^A \geq 0$.

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

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

¹⁰ We study extensive margin decisions to highlight worker selection into different jobs. However, the setup generalizes to intensive margin decisions, for example, by considering every worker supplied as a time unit.

¹¹ 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).

¹² We assume away that sophisticated workers apply for costly jobs, anticipating that paternalistic employers will protect them from mistakes. This assumption is consistent with empirical evidence: Anticipating discrimination to make inferences about job costs requires extensive contingent reasoning, which a large literature suggests is rare; see Niederle and Vespa (2023) for an overview. Since workers do not anticipate paternalistic discrimination, employers do not worry about workers' preferences for being "paternalized."

¹³ Our model is also flexible enough to allow the other-regarding utility to vary with ability, for example, by considering high- and low-skilled workers as separate groups with different welfare weights α_{kg} .

¹⁴ We relax this assumption in the structural model.

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

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

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

with $\mathcal{W}_{kg} \in \{\mathcal{W}_{kg}^{E:A}, \mathcal{W}_{kg}^E\}$.¹⁵

2.2 Defining Discriminatory Preferences

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

1. *Taste-based discrimination*: $d_{km} > d_{kf}$. The employer receives more (or less negative) non-pecuniary returns from hiring male over female workers.
2. *Statistical discrimination*: $\frac{\partial Y^E}{\partial L_{km}} > \frac{\partial Y^E}{\partial L_{kf}}$. The employer expects to receive higher revenues from the marginal male than the marginal female worker.
3. *Other-regarding discrimination*: $\alpha_{km} \mathcal{W}_{km} > \alpha_{kf} \mathcal{W}_{kf}$. The employer expects to receive higher other-regarding utility from the marginal male than the marginal female worker. This is deferential if employers use their perception of workers' perception of worker welfare and paternalistic if employers use their own perception of worker welfare.

Other-regarding discrimination arises because an employer places a higher weight on men's welfare than women's or because an employer expects men's welfare to be higher than women's. Three different mechanisms could explain why employers expect men's welfare to be higher even in the same role with the same wages: employers may (i) believe men have lower costs than women (using either the employers' first- or second-order beliefs), (ii) have different risk preferences for men and women ($u_{km}^E \neq u_{kf}^E$), and/or (iii) engage in selection neglect, i.e., they do not condition on ($\mathcal{W}_{kg}^{E:A}$) and thus overestimate workers' job costs.¹⁶

We consider other-regarding discrimination to be distinct from taste-based discrimination because, unlike taste-based discrimination, it varies predictably with perceptions of job costs c_{igk} . We consider other-regarding discrimination to be distinct from statistical discrimination because, unlike statistical discrimination, it can arise even without uncertainty, i.e., when $\mathcal{W}_g = \mathcal{W}_{kg}^{E:A} = \mathcal{W}_{kg}^E$.¹⁷

¹⁵ 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.

¹⁶ Since other-regarding discrimination is a function of the conditional expectation of cost, discrimination can result from differences between men and women in features of the cost distribution, such as variance, even when mean costs are the same.

¹⁷ Note that other-regarding discrimination can only lead to restricting the employment opportunities of willing

2.3 Comparative Statics in Gender-Specific Costs and Wages

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

2.3.1 Labor Supply

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

2.3.2 Labor Demand

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

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

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

Deferential and Paternalistic Employers and Costs Second, we assess how the demand response to changes in gender-specific costs differs between deferential and paternalistic employers. If employers are deferential (i.e., if they internalize their perception of the workers' perception of worker welfare, $\mathcal{W}_{kg}^{E:A}$), then their other-regarding utility is weakly lower when workers receive an amenity rather than a subsidy that allows them to afford the amenity (appendix A.3). Workers are weakly better off receiving the subsidy, as they can use their own valuation of the amenity to decide whether to purchase it. Therefore, if employers demand less

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 fail to correct their biased beliefs (e.g., if they never observe women working the night shift). Moreover, even with perfect information, employers may maintain different preferences over the risks workers face than the workers themselves.

gender g labor with the subsidy, they must be paternalistic. In other words, they must use their own beliefs or preferences to evaluate their other-regarding utility.

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

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

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

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

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

2.3.3 Equilibrium Wages

The effect of increases in gender-specific costs on equilibrium wages depends on the magnitude of the cost elasticity of supply relative to that of demand. Gender-specific costs decrease both labor demand and supply, reducing the equilibrium labor quantity of that gender. However, gender-specific costs might increase or decrease equilibrium wages depending on the ratio of the supply and demand elasticities with respect to gender-specific costs (see derivations in appendix A.6). If the ratio is sufficiently small, 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 supply elasticity with respect to gender-specific costs is proportionally smaller than the demand elasticity. In particular, equilibrium wages are decreasing if and only if $|\epsilon_{c_g}^S| < \delta \times |\epsilon_{c_g}^D|$, where $\epsilon_{c_g}^S$ and $\epsilon_{c_g}^D$ are the supply and demand elasticities with respect to gender-specific costs and $\delta \leq 1$ is a function of the substitutability of male and female labor and the demand and supply elasticities with respect to wages of the other gender.*

The equilibrium labor quantity and wages of the other gender do not respond to increases in gender-specific costs if male and female workers are additively separable in the production function, increase if they are substitutes, and decrease if they are complements (appendix A.7). We also derive closed-form solutions for a constant elasticity of substitution production function in appendix A.9.

The remainder of the paper tests theoretical predictions 1 to 5 in three steps. First, we experimentally vary employers’ beliefs about job costs for female workers to study the effect of paternalism on the demand for female labor. Second, we experimentally vary applicants’ beliefs about job costs for female workers to study the effect of these costs on female labor supply. Finally, we estimate the theoretical model by combining the results of both experiments to predict the equilibrium wage effects of changing job costs for female workers.

3 Setting

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

Women in Bangladesh struggle to access the labor market, particularly male-dominated occupations (BDHS, 2016; BBS, 2021).¹⁸ About 40% of working-age women in Bangladesh are employed, compared to 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)).¹⁹

¹⁸ We restrict our discussion to differences between male and female workers, though Bangladesh’s transgender or “hijra” population faces additional barriers to economic participation, as well as poor access to healthcare and exclusion from civic life (Al-Mamun et al., 2022).

¹⁹ 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).

Restrictive gender norms and labor laws also contribute to Bangladesh’s large gender employment and wage gaps. Male guardianship of females is a common feature of traditional relationships in Bangladesh, with women living under the guardianship of their fathers in childhood, their husbands and fathers-in-law in marriage, and their sons in widowhood (White, 2017). The idea of *purdah*—meaning literally veil or curtain, but figuratively used to describe women’s seclusion from the public sphere—is rooted in Islamic teachings and limits women’s access to the labor market (Lata et al., 2021).²⁰ The Bangladesh constitution establishes Islam as the state religion (US Department of State, 2022a), and the vast majority (91%) of the population identifies as Muslim (BBS, 2022).

These protective attitudes toward gender carry over into economic behavior and policies. In the 2018 Bangladesh World Value Survey, 76% of respondents agreed that “men should have more right to a job than women,” and 67% that “men make better business executives than women.” Results were broadly similar among men and women and in urban and rural areas (World Values Survey, 2018). Bangladesh law does not prohibit discrimination on the basis of gender, nor does it mandate equal pay for women and men (World Bank DataBank, 2023). Women in Bangladesh are also legally restricted from operating or cleaning certain types of machinery, carrying heavy items, or working underwater or underground (Bangladesh Labour Act, 2006). While the Bangladesh Labor Act of 2006 lifted a prohibition on women working at night, employers are still required to obtain women’s consent to work shifts between 8:00 P.M. and 6:00 A.M.; written consent is not required of men.

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

4 The Hiring Experiment: Job Costs and Labor Demand

To measure the labor demand response to variations in gender-specific costs and wages according to predictions 1 to 4 of the model, we conduct a “hiring experiment” with 495 *employers*, individuals with hiring experience in the previous three years, in Dhaka, Bangladesh. Enumerators recruit employers equally from three industries, selected based on recruitment feasibility, different perceived costs to female workers, and high levels of urban employment: manufacturing, retail/wholesale and services, and education (additional information on these industries is provided in appendix B.2).²¹ Enumerators recruit employers in person between

²⁰ Verse 4:34 of the Qur’an: “Men are the protectors and maintainers of women, because Allah has given the one more (strength) than the other, and because they support them from their means.”

²¹ 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

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 broader Bangladesh workforce (89% of managers are men, according to official statistics (BBS, 2018)). They are, on average, 32 years old (see table 1 for overall summary statistics and appendix table C.1 for summary statistics by industry). Fifty-nine percent are married, and 45% have at least one child. Furthermore, 42% have at least a Bachelor’s degree. On average, their businesses have nine male and six female employees, and they have made 27 hiring decisions in the previous three years.

Table 1: Employer Characteristics (N=495)

	Mean	S.D.
Female (%)	6.3	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 characteristics of the employers recruited for the hiring experiment. *Children* is an indicator that is 1 if the employer has at least 1 child.

“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 between 7:00 P.M. and midnight (see appendix C.2 for a photograph of the shift), with a free and safe transportation service bringing workers home in private six-seater cars after the shift. One supervisor accompanied each car.²² The applicant pool consists of 580 male and 400 female applicants aged 18 to 60, recruited at booths on 11 university campuses between February and April 2023 (see

industry: “How dangerous or unpleasant or socially unacceptable do you think this job is for [applicant name], including their commute from and to their home, with 0 indicating a very safe job, equivalent to working from home, and 10 indicating that the job is very dangerous or very unpleasant or very socially unacceptable.” The average response for female applicants was 2.5 in manufacturing, 1.0 in retail and services, and 0.3 in education.

²² The cars were mixed-gender. However, this information was not communicated to employers. Training opportunities at night are common in Bangladesh. In addition, night-shift work is becoming increasingly common as many outsourcing firms work European or US hours (Mamun et al., 2019).

appendix C.1 for a photograph of the recruitment process).²³ Applicants take two 12-minute back-to-back Excel screening tests incentivized with BDT 2 (USD 0.02) per correct answer for a total of up to BDT 40 (USD 0.4).²⁴ On average, male applicants in our experiment are 25 years old and female applicants are 24 years old (table 2). Around one fifth of applicants are married (19% of male and 23% of female applicants), and 12% have children. Female applicants are slightly less experienced than male applicants (89% have up to three years of experience versus 80% of male applicants) but have similar education (36% have a Bachelor’s degree versus 39% of male applicants) and Excel screening scores (25%, on average, versus 23% among male applicants). Because we measure within-applicant treatment effects, we do not require balance in observables across gender.

Table 2: Applicant Characteristics in the Hiring Experiment by Gender

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

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

4.1 Hiring Experiment Design

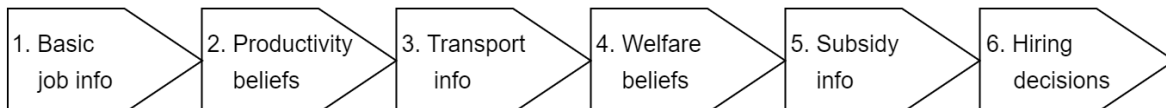
Employers make real hiring decisions and are randomized into different treatment conditions that experimentally vary the perceived job costs for workers, the payoffs received by workers, and the payoffs received by employers. This allows us to test whether employers hire fewer women when the job costs are perceived to be high (prediction 1)—even when workers can afford safe transport themselves (prediction 2). The variation in payoffs to workers and employers allows us to test whether employers react more to profit than to other-regarding concerns (prediction 3). The experiment was carefully designed to avoid potential ethical concerns

²³ We initially targeted 585 men and 405 women to construct 45 hiring pools of nine female and 13 male applicants each (we oversampled men to make hiring choices more realistic); however, five hiring pairs were excluded from the sample as the female applicant was miscoded as male. Results are unchanged when including these five pairs. We conducted recruitment on university campuses anticipating a high concentration of job seekers and that paternalistic discrimination may be particularly consequential for job seekers early in their careers. We do not restrict participation to university students.

²⁴ The tests were designed based on a scoping survey with 20 office employers about desired Excel skills.

associated with placing workers in potentially dangerous situations; see appendix B.1. The experiment takes an average of 64 minutes and is conducted in six stages (figure 1).

Figure 1: Stages of the Hiring Experiment



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

1. **Basic job information:** In the first stage, we provide employers with basic information about the job. Employers receive the following information about the hiring process: (i) Applicants have applied 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.
2. **Productivity beliefs elicitation:** In the second stage, we elicit employers’ incentivized beliefs about the on-the-job productivity of four randomly selected applicants (two male-female pairs). Employers predict the number of tasks that each applicant will complete if hired based on their first names, gender, marital status, education, years of experience, and Excel screening test scores (see appendix figure C.3 for the experimental interface).²⁵ Employers are informed that two of these applicants are randomly selected for hire and that they will receive a bonus payment for correctly predicting the productivity of these applicants. Employers guess (i) the probability that each applicant shows up to the shift (incentivized using the binarized scoring rule, see Hossain and Okui 2013), and (ii) the number of completed tasks conditional on attendance (incentivized with BDT 10, USD 0.1, for guesses within five percentage points from the truth). 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 main sample of 495 *Hiring* employers do not differ from those of 80 separately recruited *Prediction-Only* employers

²⁵ 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.

who make no hiring choices and therefore have no incentive to adjust their predictions to their hiring choices.

3. **Transport information randomization:** In the third stage, we randomize employers into one of two transport treatments that experimentally vary their perception of workers' job costs while holding constant the perceived worker selection and productivity:
 - (a) *Transport* (50%): Employers are informed about the transport with supervisors.
 - (b) *No Transport* (50%): Employers are not informed about any transport.

The randomization allows us to test theoretical prediction 1: Demand for female labor is lower without safe transport. To hold constant the perceived selection of applicants willing to work across treatments, we inform employers that all applicants have applied for the job without knowing about the transport. To hold constant the perceived productivity of applicants across treatments, we inform employers in the *Transport* treatment that workers will only learn about the transport after completing the shift, i.e., that the transport cannot affect their probability of attendance or their on-the-job performance. To ensure that differences in hiring are not driven by differences in reputation concerns, i.e., employers being concerned about being made responsible if something happens to a female worker without transport, we ensure employers that all hiring choices are private and anonymous.²⁶ To hold constant beliefs about applicants' beliefs across treatments, i.e., to ensure that employers in the *No Transport* treatment know that applicants do not expect transport, we inform employers in both treatments "Aside from the job description before, no other benefits (such as flexible hours, work-from-home, [transport], or future employment) are offered to any applicant." ("transport" is only included in the *No Transport* treatment). We verify comprehension of the experimental set-up with five comprehension questions administered after the treatment assignments (see appendix section B.6.1). We also find that employers perceive workers to be very likely to take the offered transport (i.e., high compliance) and no evidence for information spillovers (i.e., no contamination).²⁷

4. **Cost beliefs elicitation:** In the fourth stage, we elicit employers' beliefs about the job costs (including the commute) in terms of danger, unpleasantness, and social acceptability on a scale from 0 to 10. We elicit employers' beliefs for the same four applicants for

²⁶ We also find that only four employers choose reputation concerns as one of their drivers for their hiring choices.

²⁷ Only one *Transport* employer believes that applicants will not take the transport. To prevent information spillovers (i.e., employers in the *No Transport* condition learning about the transport from previous workers), we started the shifts only after roughly half (57%) of the hiring experiment was completed (results are robust to restricting the sample to all employers surveyed before this shift). Only six employers in the *No Transport* treatment believe that applicants will get home by provided transport (three of these are excluded from the analysis due to incorrectly answering understanding questions used for screening comprehension). The vast majority of *No Transport* employers (98%) believe applicants will use public transport or a ride share (Uber, CNG, Rikshaw).

whom they make productivity predictions (see appendix figure C.4 for the experimental interface). To reduce anchoring, we do not inform employers of applicants' reported costs, nor do we attach any experimental incentives to the elicitation in order to reduce strategic reporting.²⁸ We find no significant differences between *Hiring* and *Prediction-Only* employers, suggesting that our results are not driven by strategic misreporting to justify hiring decisions.

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

- (a) *No Subsidy* (40%): Male and female workers receive BDT 1,500 (USD 15) for completing the shift. Employers receive BDT 500 (USD 5) for hiring any worker.
- (b) *Male Worker Subsidy* (20%): Male workers receive BDT 2,500 (USD 25), and female workers BDT 1,500 (USD 15) for completing the shift. Employers receive BDT 500 (USD 5) for hiring any worker.
- (c) *Female Worker Subsidy* (20%): Male workers receive BDT 1,500 (USD 15), and female workers BDT 2,500 (USD 25) for completing the shift. Employers receive BDT 500 (USD 5) for hiring any worker.
- (d) *Employer Subsidy for Hiring Women* (19%): Male and female workers receive BDT 1,500 (USD 15) for completing the shift. Employers receive BDT 500 (USD 5) if their hired worker is a man, and BDT 1,500 (USD 15) if it is a woman.
- (e) *Employer Subsidy for Hiring Men* (1%): Male and female workers receive BDT 1,500 (USD 15) for completing the shift. Employers receive BDT 1,500 (USD 15) if their hired worker is a man, and BDT 500 (USD 5) if it is a woman.

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

We take the following steps in order to hold both perceived worker selection and productivity constant across subsidy treatments. First, employers draw a piece of paper to de-

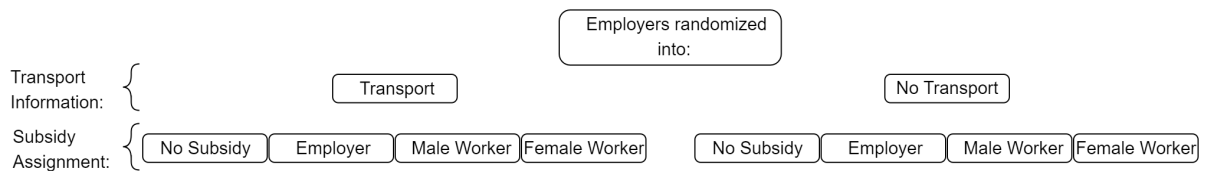
²⁸ For example, if we promised to convey the response as advice to the applicant, employers with a strong distaste for hiring women might misleadingly report a high cost.

termine their treatment assignment. This procedure signals to employers that all subsidy outcomes are due to chance. Second, the *Employer Subsidy for Hiring Men* is included to prevent asymmetrical subsidies that could signal that women and men are differentially qualified (enumerators describe all treatments but not the relative frequencies (in parentheses) to the employers). Third, in order to hold perceived selection and productivity constant, employers are informed that workers will be surprised by the subsidies at the end of the shift.

6. **Hiring:** In the sixth stage, employers make twelve hiring decisions, each between two randomly selected applicants. For each applicant, employers are shown the same characteristics as employers in the prediction questions (see appendix figure C.5 for the experimental interface and appendix figure C.6 for the experimental interface when we reduce the salience of gender, discussed below). Each employer makes decisions for two male–male pairs and ten mixed-gender pairs in random order. We did not include two female–female pairs because we wanted to keep the female-to-male ratio similar to that observed in labor markets in Bangladesh. Two mixed-gender pairs were already included in the productivity and cost beliefs elicitation stages. One of these two pairs comes from the application experiment (described in section 5) to incentivize productivity beliefs (see stage 2). The remaining 11 pairs are shown to 11 employers each, implementing a different pair per employer so that we implement one hiring choice per pair (see appendix B.5 for a description of the matching process). Employers are informed that one of their decisions will be implemented and that their identity will not be revealed to any workers.

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

Figure 2: Treatments: Varying Information about Transport and Worker and Employer Pay



Notes: Employers were cross-randomized into two transport and four subsidy treatments, described in detail above. First, we randomize employers into one of two transport treatments. Employers in the *Transport* treatment were informed that the job provided all workers free and safe transport home after the shift. Employers in the *No Transport* treatment were not informed about the transport. Second, we randomize employers into one of four subsidy treatments. Employers in the *No Subsidy* treatment were not informed about any cash subsidies.

Employers in the *Employer Subsidy* treatment were informed that every time they hired a woman, the employer would receive a cash subsidy. Employers in the *Male Subsidy* and *Female Subsidy* treatments were informed that every time they hired a male or female worker, the worker would receive a surprise cash subsidy.

4.2 Hiring Analysis: Empirical Specification

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

We identify *within-applicant* differences in hiring across treatments, allowing us to rule out a myriad of endogeneity concerns (though balance is not required, we provide applicant characteristics by treatment in appendix table C.3). The transport treatment was stratified by applicant and by employer industry.²⁹ We restrict the sample to employers who answer all understanding questions correctly (94%, see appendix B.6.1 for the understanding questions) and who are not assigned to the *Employer Subsidy for Hiring Men*, a treatment we only include for perceptions of fairness and symmetry (see section 4.1). Employer characteristics and productivity beliefs are balanced across treatment arms (appendix tables C.2 and C.3) and predictions do not differ between *Hiring* and *Prediction-Only* employers (appendix table C.4). In addition, employers are more likely to report basing their hiring decisions on safety but not taste or statistical concerns without transport (employers in the *Female Subsidy* expected women to generate slightly lower revenues: BDT 29, USD 0.3, $p = 0.04$).

We estimate the following equation among all female applicants shown to at least two employers:³⁰

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

where H_{ki} is an indicator that is 1 if employer k hires female applicant i . NT_k , MS_k , FS_k , and ES_k are indicators that are 1 if employer k is assigned to the *No Transport*, the *Male Subsidy*, the *Female Subsidy* or the *Employer Subsidy* treatment, respectively. μ_i and μ_j are strata fixed effects, i.e., female applicant and employer industry fixed effects.³¹ We estimate Huber–White robust standard errors clustered at the employer level (the level of randomization).

As each pair was shown to 11 different employers, this specification allows us to test whether employers from the same industry hire the same woman compared to the same man differentially across treatment arms. Specifically, we test:

²⁹ As the subsidy treatments were drawn on-the-spot, they were not stratified.

³⁰ We exclude seven female applicants from the application experiment (used to incentivize beliefs, see section 4.1, stages 2 and 4) shown to only one employer. By design, all applicants in the hiring experiment were shown to multiple employers.

³¹ We also control for a vector of male applicant characteristics (Excel screening score, education, work experience, and marriage status) in the 12th prediction pair, in which applicants were not always compared to the same man.

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

The first prediction implies that employers are other-regarding. Without taste, profit, or reputation concerns, employers do not have *self*-regarding motives to hire fewer women without transport. The second prediction implies that employers are paternalistic. A differential employer's utility from hiring women relative to men is strictly greater in the *No Transport+Female Subsidy* treatment than the *Transport+No Subsidy* treatment. Independent of women's and men's valuation of transport, women are strictly better off (they receive a subsidy larger than the cost of transport) while men are strictly worse off (they do not receive transport). Employers may only hire fewer women with the subsidy than the transport if they expect to earn less other-regarding utility because they (i) perceive the subsidy's value to be lower than that of the transport, and (ii) believe women may not purchase the transport because they undervalue it. The third prediction implies that labor demand is locally downward sloping in wages.

Finally, we assess heterogeneity in hiring by employer characteristics; 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.

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

1. Employers who reported above-median agreement with paternalistic laws in India that restrict women from working at night (on a 0–10 scale with a median response of 8).
2. Employers who reported above-median agreement with the statement that women should not work at night, even if they want to (on a 0–10 scale with a median response of 6).
3. Employers who transferred above-median amounts to the female worker in a three-way dictator game between themselves and two workers from the application experiment (to ensure that employers did not simply try to compensate workers for not hiring them; BDT 0–100 with a median transfer of BDT 30 or USD 0.3 to male and female workers).³²

³² Dictator game transfers are not a direct measure of α_{kg} . In our model, employers should keep the entire amount whenever $\alpha_{kg} < 1$. Instead, we consider the dictator game transfers as a proxy of underlying individual-level other-regarding preferences.

4. Employers who 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 response of 10).

We also test whether the response to the transport and subsidies is larger among employers with an above-median Kling Mean effects index of the four measures (Kling et al., 2007).³³

These heterogeneity analyses also serve a second purpose: If treatment effects are larger among employers with more other-regarding attitudes towards women, then the observed behavior likely reflects true underlying other-regarding preferences rather than, for example, experimenter demand effects. 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.

4.3 Results: Job Costs and Labor Demand

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

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

Consistent with prediction 1, not informing employers about the transport reduces the share of hired female applicants by 22% (–10ppts, $p < 0.01$) from a baseline of 45% (figure 3, bars 1 and 2).³⁴ The reduction in demand for female labor seems to be driven by changes on the intensive rather than the extensive margin: Employers in the *No Transport* hire about one fewer woman, on average, ($p < 0.01$, appendix table C.6).

As employers only make hiring choices about applicants willing to take the job, these results imply that employers restrict women’s employment opportunities when employers consider the opportunities unsafe. Moreover, we find that this employer behavior varies with both employer and applicant characteristics: Employers respond more strongly to the transport information when they are male (even though the difference is insignificant given the small number of female employers), have more hiring experience (appendix figure C.9), or when the female applicant has less experience than the male applicant (appendix figure C.10).³⁵

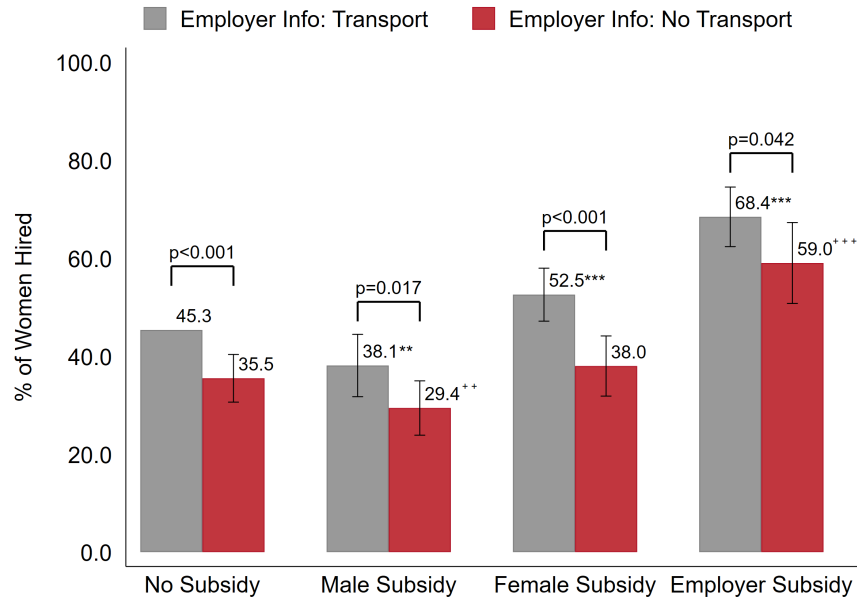
³³ We find similar results when using a correlation-adjusted index (Anderson, 2008).

³⁴ The high female hiring rate is consistent with responses to an open-ended question suggesting that employers believed the study’s goal was to test their ability to hire the most qualified workers. Accordingly, the enumerators reported that the employers attempted to reduce their biases against women as much as possible.

³⁵ The employer heterogeneity may be driven by employers with more hiring experience believing that women have significantly higher costs than employers with less hiring experience ($p < 0.01$) and female employers

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

Figure 3: Hiring by Transport Information and Subsidy Assignment



Notes: The graph shows results from equation 3, i.e., the share of women hired by whether the employer knows about the transport or was offered no subsidy, a male or female worker subsidy, or an employer subsidy for hiring women. Each bar is the sum of the control mean and the relevant regression coefficients. We show 95% confidence intervals based on the estimated standard errors of the linear combinations of the regression coefficients. Asterisks are from p -values from Wald tests comparing hiring rates between *No Subsidy* and each of the subsidies with transport, $p < 0.10^*$, $p < 0.05^{**}$, $p < 0.01^{***}$ (on the gray *Transport* bars, only), and pluses from comparing *No Subsidy* and each of the subsidies without transport, $p < 0.10^+$, $p < 0.05^{++}$, $p < 0.01^{+++}$ (on the red *No Transport* bars, only). P -values between bars compare hiring rates with and without transport within subsidies.³⁶

Using the change in hiring in response to applicant characteristics and the subsidy treat-

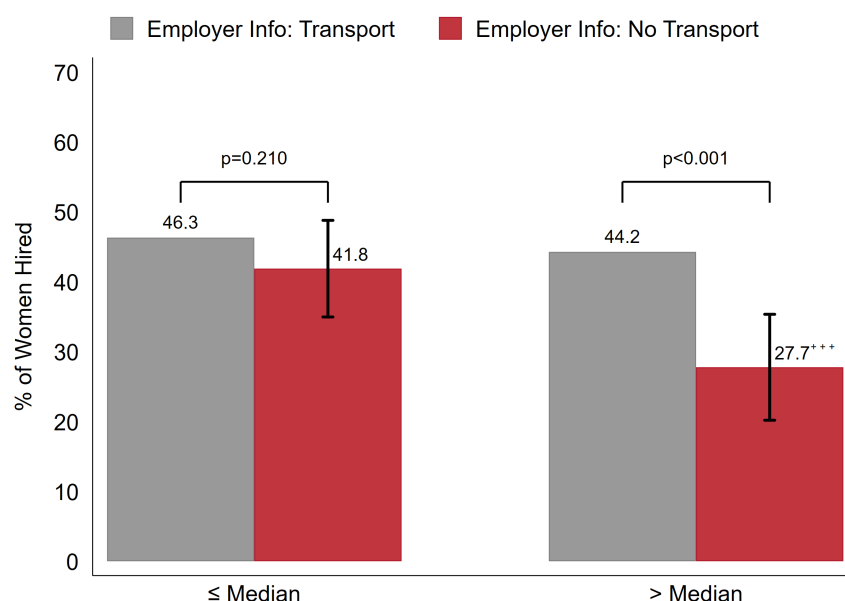
believing that women are more risk-seeking than male employers ($p = 0.02$). We do not find evidence that information about the ride affects employers hiring decisions between male-male applicant pairs, suggesting that paternalistic discrimination is a function of gender rather than characteristics (such as inexperience) associated with gender.

³⁶ The p -values comparing the effect of the female with the male subsidy, with and without transport, are $p = 0.99$ and $p = 0.49$, respectively (not shown). The p -values comparing the effect of the female with the employer subsidy, with and without transport, are $p < 0.01$ and $p < 0.01$, respectively (not shown).

ments, we estimate employers' valuation of the transport in terms of worker qualifications and payments to female workers or employers themselves. The coefficients on the Excel screening score, the *Female Subsidy*, and the *Employer Subsidy* imply that employers value the safe transport as much as a 7ppts (0.5SD) increase in Excel score, BDT 1,371 (USD 13) to the worker, or BDT 427 (USD 4) to the employer (appendix table C.5, columns (1) and (2)).

Finally, consistent with prediction 4, employers with stronger other-regarding preferences respond more strongly to the *No Transport* treatment (figure 4) and directionally more to the *Female Subsidy* for three out of four measures (appendix figure C.8). Overall, we do not find substantial heterogeneity for two measures, for which we also observe little heterogeneity in the underlying responses, making meaningful employer classification difficult: Consistent with the 50–50 norm (Andreoni and Bernheim, 2009), 71% of employers gave the same dictator game transfers to men and women (85% within BDT 10), and 59% fully agreed (10 out of 10) that women should be protected against their will (only 4% disagreed, 0–4 out of 10).³⁷

Figure 4: Hiring by Transport Information and Other-Regarding (Deferential or Paternalistic) 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)

Results are robust to a series of different regression specifications (appendix table C.5). They are robust to (i) removing applicant fixed effects or (ii) all covariates, and (iii) selecting covariates using Belloni et al. (2014)'s post-double selection Lasso method. They are also

³⁷ A body of literature questions the value of the dictator game for measuring altruism, suggesting that giving may be an artefact of the experimental environment with little external validity (Cherry et al., 2002; Bardsley, 2008; Di Tella et al., 2015; Winking and Mizer, 2013).

robust to including (vi) employers who answer understanding questions incorrectly, (v) only employers who report that women in the *Transport* treatment will get home using provided transport and women in the *No Transport* will not, and (vi) only employers surveyed before the first night shift (for whom spillovers are impossible). They are also robust to (vii) excluding the applicants from the application experiment. Finally, results are robust to (viii) clustering standard errors at both the employer and applicant level (Cameron et al., 2011) and (ix) using a Logit specification.

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 (see appendix figure C.6 for the experimental interface).³⁸ This result is consistent with enumerator reports that employers made a conscious effort to reduce their biases against women as much as possible in the main study when the experiment’s relationship to gender was more salient. Thus, reducing the salience of gender in the experiment *increases* paternalistic discrimination. By contrast, if the results were driven by experimenter demand effects, reducing the salience of gender in the experiment should *reduce* paternalistic discrimination.

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).

1. **Value of Job Costs:** As we discussed in section 4.3, employers assess the value of job costs (on a 0–10 scale, see section 4.1, stage 4) to be significantly higher without transport than with transport, and more so for women than men.

Employers also believe women underestimate value of job costs more than men, both on the extensive and intensive margin. We elicited first- and second-order beliefs about job costs from 80 *Beliefs-Elicitation* employers, who guessed productivity and costs for eight applicants from the application experiment (second-order beliefs were incentivized with BDT 5, or USD 0.05, per correct answer).³⁹ Employers believe that both men and women underestimate the costs ($p < 0.01$). In addition, 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 (the difference between first- and second-order beliefs) is 1.8 for women versus 1.4 for men ($p < 0.01$).⁴⁰ Female

³⁸ 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.

³⁹ These employers are different from the 80 *Prediction-Only* employers who made predictions about applicants from the hiring experiment.

⁴⁰ Note that we do not observe true costs on the Likert scale.

employers do not believe that women make larger conditional mistakes than men, which is consistent with the absence of a transport treatment effect for them.

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

2. **Risk Preferences:** Employers who believe *women should be* relatively risk-averse (above-median in our sample of employers) but not employers who believe *women are* relatively risk-averse reduce hiring significantly more without transport (see appendix figure C.11). 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]?"⁴¹

These results suggest that risk preferences may drive paternalistic discrimination, and offer additional evidence that employers are paternalistic rather than deferential.⁴²

3. **Selection Neglect:** We find no evidence that selection neglect drives paternalistic discrimination in the experiment. We test for selection neglect by eliciting employers' perceptions of differences in reported job costs between applicants willing and unwilling to take the job at BDT 1,500 (USD 15) in the application experiment (see section 4.1, stage 4). If selection neglect drives discrimination (e.g., by causing employers to evaluate the selected pool of willing applicants as if they were a random draw from the general population), we would expect employers who underestimate the cost differences to respond more strongly to treatment (see, for example, Exley and Nielsen (2022)). However, we find that employers overestimate the reported cost differences between willing and unwilling applicants (2.3 for women and 1 for men, $p < 0.01$, compared to the true values of 0.8 and 0.5) and that hiring behavior does not vary with the perceived difference (see appendix figure C.11).

Overall, our experimental results in the hiring experiment suggest that employers engage in

⁴¹ We opted not to elicit incentivized risk preferences because gambling is illegal in Bangladesh.

⁴² We do not believe that low reported risk-preferences for women simply proxy low perceived costs for women or paternalistic attitudes. We observe a very low correlation between risk-preferences and perceived costs ($r=-0.02$) and low correlations between risk-preferences and agreement with paternalism laws in India ($r=-0.12$), the statement that women should be protected even against their will ($r=-0.08$), and the statement that women should not work at night ($r=-0.18$).

substantial paternalistic discrimination, which is primarily driven by employers beliefs that 1) job costs are high and women underestimate them, and 2) women should be more risk-averse. In the next section, we investigate how applicants respond to changing the job costs to female workers in the application experiment.

5 The Application Experiment: Job Costs and Labor Supply

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

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

Table 3: Applicant Characteristics in the Application Experiment by Gender

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

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

5.1 Application Experiment Design

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

1. **Applicant screening:** In the first stage, applicants take two 12-minute back-to-back Excel screening tests incentivized with BDT 2 (USD 0.02) per correct answer for a total compensation of up to BDT 40 (USD 0.4). After completing the tests, applicants are informed that the workshop and job will be from 7:00PM to midnight, that all hired workers will receive an Excel certificate of completion, and a fraction of workers will be promoted and receive a promotion benefit of BDT 500 and a promotion certificate.
2. **Transport information randomization:** In the second stage, we randomize applicants into one of two transport treatments that experimentally vary the perceived job costs:⁴³
 - (a) *Transport:* Applicants are informed about the safe transport home.
 - (b) *No transport:* Applicants are not informed about the safe transport home.
3. **Cost beliefs elicitation:** In the third stage, we elicit applicants' unincentivized beliefs about job costs (see section 4.1).
4. **Reservation wage elicitation:** In the fourth stage, we elicit applicants' reservation wages using the Becker–DeGroot–Marschak mechanism (Becker et al. (1964), see figure C.7 for the experimental interface). Applicants then randomly draw a wage between BDT 100 (USD 1) and BDT 5,000 (USD 50) from the following distribution (applicants are informed about the wages in the distribution but not the probability of drawing each wage):⁴⁴

Table 4: Random Wage Distribution in the Application Experiment

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

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

⁴³ 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 hired for the job are promoted. In the *Low (High) Promotion* arm, promotions are conducted automatically, selecting the 10% (90%) highest-scoring workers. Applicants determine their promotion treatment assignments by drawing a piece of paper, signaling to them that all promotion assignments are due to chance.

⁴⁴ We noticed a correlation between the random lottery wage and applicant characteristics mid-survey. In particular, women, educated applicants, and married applicants without children drew higher random wages on average. We were concerned that enumerators might be redrawing the wages to draw higher wages for applicants with higher opportunity costs. We discussed our concerns with the survey firm and started closely supervising the surveys. Enumerators never redrew a wage while we were watching, and we do not observe any correlation between the stated reservation wage and the randomly drawn reservation wage.

5.2 Application Analysis: Empirical Specification

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

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

$$\bar{w}_i = \alpha + \beta_1 NT_i + \beta_2' X_i + \epsilon_i \quad (4)$$

where \bar{w}_i is the stated reservation wage of applicant i , and NT_i is an indicator that is 1 if applicant i is assigned to the *No Transport* treatment. X_i is a vector of applicant controls (as randomization was across applicants), including the applicant's age, Excel screening score, education, years of experience, and marital status.⁴⁵ ϵ_i are Huber–White robust standard errors.

5.3 Results: Job Costs and Labor Supply

We first test whether information about the transport changed applicants' beliefs about job costs and then whether exogenously changing perceived job costs changes application decisions. Not informing applicants about the transport increases their perceived job costs by 0.4 points ($p > 0.1$) from a baseline of 2.3 among male applicants and by 0.8 points ($p = 0.03$) from a baseline of 5.9 among female applicants (on a scale from 0–10, appendix table C.7).

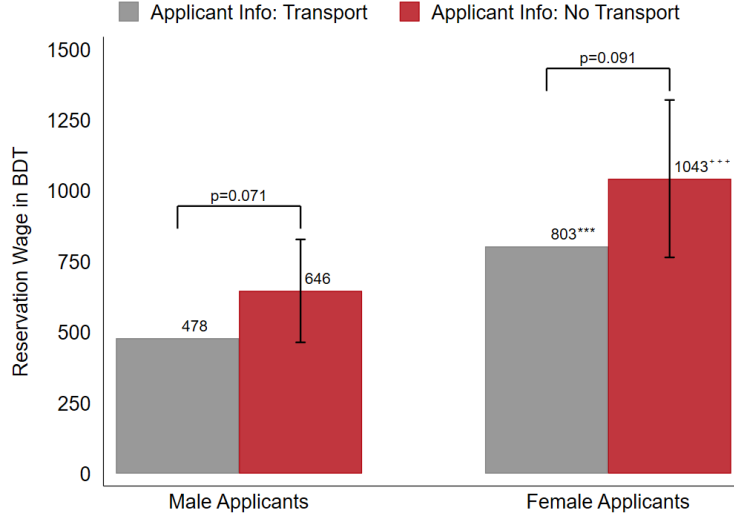
Not informing applicants about the transport increases the reservation wage of male applicants by 35% (BDT 168, USD 2, $p = 0.07$) from a baseline of BDT 478 (USD 5) and that of female applicants by 30% (BDT 240, USD 2, $p = 0.09$) from a baseline of BDT 803 (USD 8, figure 5). Women's significantly higher reservation wage with transport ($p < 0.01$) is consistent with women's higher perceived costs even with transport. Interestingly, the valuation of the transport by both male and female applicants is similar to the expected transport price in Dhaka, suggesting that the applicants considered safe transport as a means of reducing their transport costs. By contrast, employers value the transport significantly more for female workers, at BDT 1,371 (USD 13, $p < 0.01$, section 4.3).⁴⁶ Starting from a baseline wage of BDT 1,500 (USD 15), the wage paid in the experiment, male labor supply decreases by 5% (4ppts, $p > 0.01$) without transport and female labor supply by 15% (13ppts, $p = 0.06$, appendix table C.8).

⁴⁵ 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 43).

⁴⁶ This is not driven by the different selection of applicants in the two experiments: (i) women with any reservation wage in the application experiment versus (ii) women with a reservation wage of \leq BDT 1,500 in the hiring experiment, where women knew ex-ante they would be paid BDT 1,500. In fact, we find that women with a reservation wage of \leq BDT 1,500 in the application experiment react even less to the transport treatment than women with a reservation wage of $>$ BDT 1,500 (appendix table C.8).

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

Figure 5: 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 Structural Estimation

To quantify the effect of paternalistic discrimination on equilibrium wages and employment, we combine the results from the labor demand and supply experiments described in the previous two sections in an equilibrium model. The model allows us to identify the equilibrium effects of changing perceived costs for workers when allowing worker selection and productivity to vary with costs. First, we construct the labor demand function using employers’ decisions in the hiring experiment. Second, we construct the labor supply function using applicants’ reservation wages in the application experiment. Finally, we combine the demand and supply functions to construct equilibrium employment rates and wages for men and women in a hypothetical market, to benchmark the importance of paternalistic discrimination and assess the effectiveness of safe transport and subsidy interventions.

6.1 Labor Demand

We simulate the labor demand function in three steps. First, we estimate employers' preference parameters, i.e., how employers trade off taste, profit, and other-regarding concerns in hiring decisions. Second, we estimate how employers' beliefs about worker productivity and welfare respond to changes in wages and transport. Third, we use the estimated preference parameters and predicted beliefs to simulate labor demand.

6.1.1 Parametrization

We model the preferences of paternalistic employers from equation 2. We allow employers' profit and welfare beliefs to vary with wages and transport. We treat labor markets for each industry and gender separately such that each market is a gender-industry combination. Employers and workers do not move between industries. The markets for male and female labor clear simultaneously by industry. We normalize d_{jm} to zero and drop the gender subscript such that d_j is the employer's taste for working with women relative to men.

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

$$u_{ki} = \underbrace{d_j}_{\text{Taste utility}} + \underbrace{\beta_j \Pi_{ki}(w_{jg}, NT_{jg})}_{\text{Profit utility}} + \underbrace{\alpha_{jg} \mathcal{W}_{ki}^E(w_{jg}, NT_{jg})}_{\text{Other-regarding utility}} + \varepsilon_{ki} \quad (5)$$

$$= v_{ki} + \varepsilon_{ki}$$

where v_{ki} is the utility that varies according to the applicant's gender, expected profit, and other-regarding utility, and ε_{ki} is an unobserved demand shock. The employer's *preference parameters* 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 profit and welfare are given by $\Pi_{ki}(w_{jg}, NT_{jg})$ and $\mathcal{W}_{ki}^E(w_{jg}, NT_{jg})$.

6.1.2 Estimating Employers' Preference Parameters

We estimate employer preference parameters using a binary choice model. 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:

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

where v_{ki} is the non-random utility of employer k from hiring applicant i in equation 5. Assuming an Extreme Value Type 1 distribution for the unobserved demand shock ε_{ki} in equation 5, we estimate preference parameters $(d_j, \beta_j, \alpha_{jm}, \alpha_{jf})$ using logistic regression based on the

10 binary hiring decisions of each employer in the experiment.⁴⁷ We present results in money-metric utility (to the employer) by dividing d_j , α_{jm} and α_{jf} by β_j . We calculate standard errors using the delta method.

We estimate equation 5 using the variation in employers' expected profits, Π_{ki} , and welfare, \mathcal{W}_{ki}^E . We calculate employers' profit and welfare expectations using the predictions from the *Hiring* employers for the four applicants for whom employers made both predictions and hiring choices (section 4.1, steps 2 and 4).

First, we calculate employers' expected profits Π_{ki} as the expected revenue generated by the worker in addition to any subsidy payments. The expected revenue is the sum of the employers' base pay of BDT 500 (USD 5) and a piece rate of BDT 5 (USD 0.05) multiplied with the predicted number of tasks completed (the incentivized expected attendance rate multiplied by the incentivized expected conditional number of tasks completed; see section 4.1, step 2). In addition to the workers' revenue, employers in the *Employer Subsidy* treatment receive an additional payment of BDT 0 for male workers and of BDT 1,000 for female workers.⁴⁸

Second, we calculate \mathcal{W}_{ki}^E as the difference between the wage offered to the worker and the expected job costs, $\mathbb{E}_k[u_{ki}^E(c_{ki}^E)]$. The wage paid to the worker is randomly assigned based on the subsidy treatment: Workers in the *No Subsidy* and *Employer Subsidy* treatments receive BDT 1,500 (USD 15), while male in the *Male Subsidy* treatment and female workers *Female Subsidy* treatment receive BDT 2,500 (USD 25). The expected job costs are the predicted job costs on a scale of 0–10 (see section 4.1, step 4) converted to money-metric using conversion rates calculated from employers' hiring responses to increases in costs and worker wages (described in appendix section B.7.1). We thus assume that costs on the Likert scale reflect both beliefs about job costs and the employer's preferences over these costs.

Results Results are shown in table 5. We find that employers internalize 11% of payments to male workers and 17% of payments to female workers. Employers in manufacturing place a larger weight on women's welfare than on that of men ($p = 0.03$).⁴⁹ We also observe a distaste for hiring women relative to men (d_j), though not statistically significant. Holding productivity and worker welfare constant, employers are willing to forego BDT 110 (USD 1) to hire a man rather than a woman.

Appendix table C.12 shows that the results are largely consistent when (i) omitting control variables, (ii) using probit rather than logit, (iii) estimating heterogeneous preferences using mixed logit, (iv) implementing a control function approach (described in appendix B.7.3), and (v) using only random employer and worker subsidies while controlling for the expected revenue and job costs.

⁴⁷ We describe the main estimation strategy in more detail in appendix appendix B.7.2. We show robustness to alternative modeling approaches in appendix C.2.

⁴⁸ Since employers do not pay the workers' wages, we do not include wages in profit calculation.

⁴⁹ Our estimated welfare weights are slightly lower than those estimated by Chen and Li (2009) in dictator games (0.32–0.47).

Table 5: Employer Preferences: Parameter Estimates

	Pooled	Manufacturing	Services	Education
d	-0.109 (0.077)	-0.021 (0.118)	-0.059 (0.226)	-0.184* (0.107)
α_m	0.112** (0.053)	0.015 (0.075)	0.266 (0.177)	0.126* (0.072)
α_f	0.169*** (0.041)	0.173*** (0.059)	0.239** (0.120)	0.143** (0.065)
$p\text{-val } (\alpha_m = \alpha_f)$	0.209	0.033	0.838	0.773
Observations	1,826	610	592	624

Notes: The table presents parameter estimates from equation 5 estimated among all mixed-gender hiring pairs. All estimates in money metric. d in '000 BDT. Standard errors are calculated using the delta method. We present p -values from testing whether α_m is statistically different from α_f .

6.1.3 Predicting Employer Beliefs as a Function of Wage and Transport

We estimate the functions $\Pi_{jg}(w_{jg}, NT_{jg})$ and $\mathcal{W}_{jg}^E(w_{jg}, NT_{jg})$, which indicate the beliefs of employers in industry j about profitability and welfare for gender g workers as a function of wage and transport, allowing the beliefs to reflect changes in applicant selection and productivity. We assume a single set of beliefs for all employers in a given industry (and thus drop subscript k).

To identify the relationship between beliefs, wages, and transportation, we estimate a random forest model in the sample of *Beliefs-Elicitation* employers who each guessed the productivity and costs for eight applicants from the application experiment (see section 4.4). *Beliefs-Elicitation* employers were provided with the same information as *Hiring* employers (applicant gender, Excel screening score, education, work experience, and marital status), in addition to the applicant's wage and transport condition. We then use this trained random forest to predict the beliefs of *Hiring* employers (see appendix section B.7.4 for additional detail). That is, we answer the question "What would the *Hiring* employers have thought about the applicant if we had allowed wages and information about the transport to affect selection and productivity?" We then calculate the expected productivity and worker costs in each industry at every wage with and without transport.

6.1.4 Constructing the Labor Demand Curve

Finally, we use the estimated preference parameters and predicted beliefs to simulate labor demand in each industry. We assume that each market consists of 495 employers, 495 male applicants, and 495 female applicants, as in the experimental set-up. Each employer chooses whether to demand (i) a male worker in the market for male labor and (ii) a female worker in the market for female labor, and earns BDT 62 per completed task.⁵⁰ In each market, the employer's outside option to hiring is not hiring and receiving zero taste, profit, or other-regarding utility.⁵¹

6.2 Labor Supply

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

$$\widehat{L}_g^S(w_{jg}, NT_{jg}) = \frac{\sum_i \mathbb{1}(\bar{w}_i(NT_{jg}) \leq w_{jg})}{\sum_i \mathbb{1}} \quad (7)$$

6.3 Counterfactuals

We conduct three sets of counterfactual analyses. First, we estimate the equilibria with and without transport. Second, we evaluate the importance of paternalistic discrimination relative to other drivers of the gender gaps in employment and wages in the experimental setting, such as supply-side differences and other forms of discrimination. Third, we estimate the cost-effectiveness of two counterfactual policies: subsidized safe transport and subsidized female wages. We consider three outcomes: worker welfare according to applicants, worker welfare according to employers, and employers' expected profits.⁵²

⁵⁰ In the experiment, employers received a piece rate of BDT 5 (USD 0.05) per task in addition to a base show-up fee of BDT 500 (USD 5). Our preferred estimate of Π_{jg} in the structural estimation eliminates the BDT 500 base profit and calibrates a piece rate that matches the expected average profits with the expected average profits in the experiment: $\widehat{\Pi}_{jg} = (5 + \frac{2,000}{\text{average productivity}}) \times \text{tasks} - w_{jg}$ (employers expect a base profit of BDT 500 at a worker wage of BDT 1,500; the associated piece rate is BDT 62 or USD 0.6). We also estimate the model under the effective payment scheme used in the experiment: $\widehat{\Pi}_{jg} = 2,000 + 5\widehat{Tasks}_{jg} - w_{jg}$ (employers expect a base profit of BDT 500 at a wage of BDT 1,500); results are shown in appendix figures C.14.

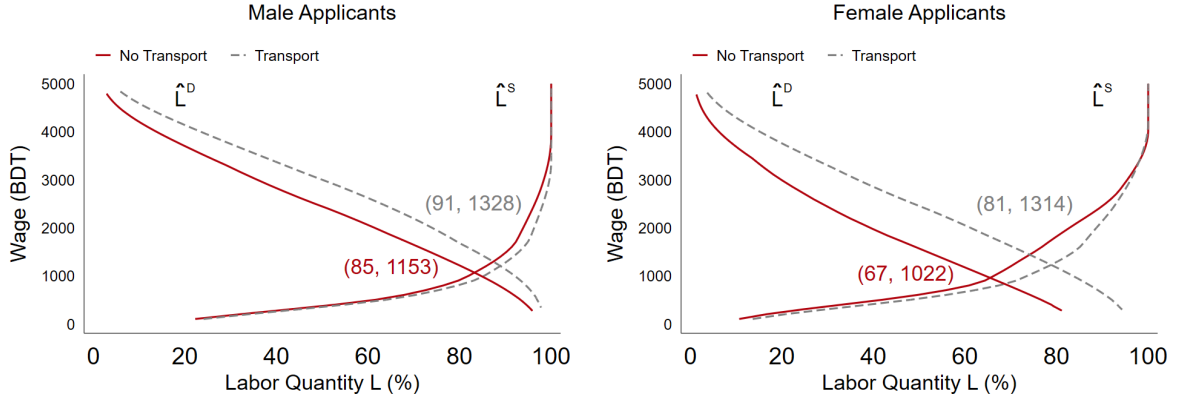
⁵¹ We thus assume that employers' preferences ($d_j, \beta_j, \alpha_{jg}$) and beliefs ($\Pi_{jg}, \mathcal{W}_{jg}^E$) are stable across hiring environments, i.e., when employers choose between one male and one female applicant or between one male or one female applicant and the outside option of not hiring. We discuss the simulation of the demand curve in appendix B.7.5.

⁵² We do not consider employer utility as an outcome, since it may include employers' discriminatory preferences. The debate over utilitarianism as a guiding principle in economics has a long history (see, for example, Sen (1979)) and is beyond the scope of this paper. See Bernheim and Taubinsky (2018) for a broader discussion of various approaches welfare analysis with behavioral agents. We use employers' beliefs about welfare and profits instead of workers' true welfare and profits because (i) true welfare is not observed, and (ii) paternalistic employers may not update their beliefs if they rarely hire women.

6.3.1 Equilibrium

Not offering transport to applicants reduces equilibrium female employment by 17% (from 81% to 67%) and female wages by 22% (from BDT 1314 to BDT 1022; figure 6; we also present results by industry and using the piece rate used in the experiment in appendix figures C.13 and C.14).⁵³ In addition, not offering transport reduces male employment by 7% and male wages by 13%. The decrease in demand for male labor is explained by two facts: (i) male and female labor is additively separable in the production function, i.e., employers do not decide between one male and one female worker, and (ii) employers expect male workers' productivity to be lower without transport (they believe male workers are less likely to attend the shift). Consistent with prediction 5, equilibrium female wages (but not male wages) decrease in some industries even when holding constant selection and productivity across treatments (appendix figure C.15).

Figure 6: 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 a piece rate of BDT 62 (USD 0.6). Numbers in parentheses in the graph give (L_g^*, w_g^*) . Numbers in gray on the right-top are the equilibrium with transport and numbers in red on the left-bottom are the equilibrium without transport.

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

We benchmark the importance of paternalistic discrimination in explaining the gender employment and wage gaps observed without transport in the experiment. We consider a series of counterfactuals that one-by-one eliminate the following sources of gender disparities in equations 5 and 7:

1. Paternalistic discrimination: Equalize other-regarding utility by (i) setting female welfare weight equal to that for men ($\alpha_{jf} = \widehat{\alpha_{jm}}$), (ii) setting expected welfare for females

⁵³ We do not model firms' entry and exit in a competitive equilibrium. Whether paternalistic firms will exit the market over time depends on a multitude of factors, including the degree of heterogeneity in preferences, the substitutability of male and female labor, and the accuracy of employers' and workers' beliefs.

equal to that for men at each wage ($\mathcal{W}_{jf}^E(w) = \widehat{\mathcal{W}_{jm}^E(w)}$), or (iii) both simultaneously ($\alpha_{jf}\mathcal{W}_{jf}^E(w) = \widehat{\alpha_{jm}\mathcal{W}_{jm}^E(w)}$). We present welfare results under employers' status quo beliefs.⁵⁴

2. Taste-based discrimination: Equalize non-pecuniary returns ($d_j = 0$).
3. Statistical discrimination: We equalize the expected profit at every wage ($\Pi_{jf}^E(w) = \widehat{\Pi_{jm}^E(w)}$).
4. Differences in labor supply: Equalize labor supply at every wage ($L_f^S(w) = \widehat{L_m^S(w)}$). We rank male and female applicants by their reservation wages and equate each female applicant's reservation wage with that of her male counterpart. We then recompute female applicants' perceived welfare using these updated wages. We also update demand estimates to account for the changes in selection and its effects on employers' productivity and welfare beliefs (see also section 6.1.3).⁵⁵

Results Paternalistic discrimination appears to be as important as statistical discrimination and more important than taste-based discrimination in our experimental setting (figure 7). Eliminating paternalistic discrimination reduces the gender employment gap by 22% (4 ppts) and reverses the gender wage gap. In addition, eliminating paternalistic discrimination increases worker welfare by 29% using workers' perceptions of their own welfare and by 4% using employers' perceptions of worker welfare (appendix table C.13). That is, paradoxically, employers agree that female workers would be better off in equilibrium without paternalistic discrimination, due to the fact that female workers would be hired at a higher wage. The effect of eliminating paternalistic discrimination seems almost entirely driven by differences in perceived welfare, as opposed to differences in the welfare weights placed on men and women.

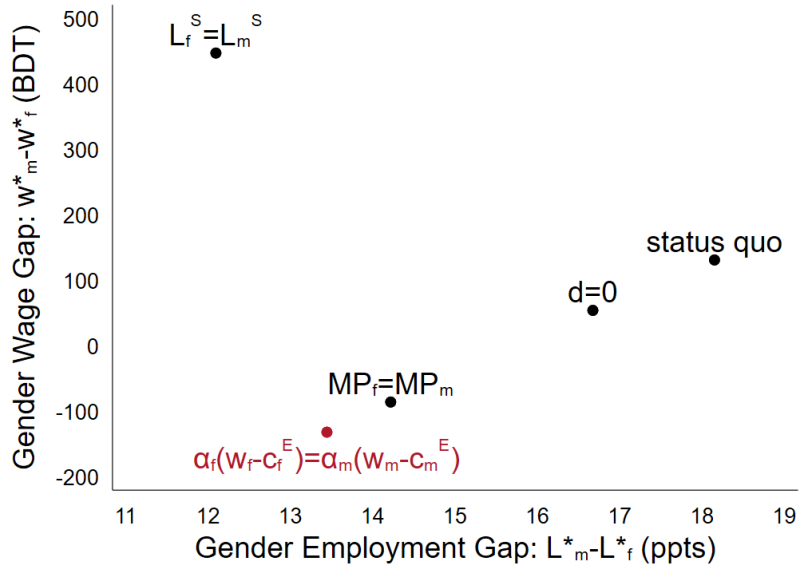
By contrast, eliminating taste-based and statistical discrimination reduces the gender employment gap by 6% (1 ppts) and 22% (4 ppts) and the gender wage gap by BDT 77 (USD 0.7) and BDT 217 (USD 2), respectively, while eliminating differences in labor supply reduces the gender employment gap by 33% (6 ppts) but increases the gender wage gap (as the increase in female labor supply puts downward pressure on female wages). Note that paternalistic discrimination may be particularly prevalent in our experiment since the night shift is highly salient; taste-based and statistical discrimination might be relatively small as women who would never work do not participate in the experiment, and employers do not meet applicants in person and receive a highly informative signal of applicant quality (the Excel screening score). By contrast, eliminating taste-based and statistical discrimination reduces the gender employment gap

⁵⁴ That is, employers in the simulation behave as if they have the same beliefs and preferences toward men and women, but they evaluate the resulting equilibrium using their original beliefs which differ by gender.

⁵⁵ After equalizing labor supply, we calculate worker welfare based on workers' simulated perceptions at the new levels of supply. This ensures that simulated workers only choose to work when their perceived welfare is positive. Hence, we put less stock in the welfare effects of this counterfactual, since the effects are largely mechanical.

by 6% (1 ppts) and 22% (4 ppts) and the gender wage gap by BDT 77 (USD 0.7) and BDT 217 (USD 2), respectively, while eliminating differences in labor supply reduces the gender employment gap by 33% (6 ppts) but increases the gender wage gap (as the increase in female labor supply puts downward pressure on female wages). Note that paternalistic discrimination may be particularly prevalent in our experiment since the night shift is highly salient; taste-based and statistical discrimination might be relatively small as employers receive a highly informative signal of applicant quality (the Excel screening score) and do not interact with applicants directly.

Figure 7: Benchmarking Paternalistic Discrimination



Notes: The graph shows the gender employment gap ($L_m^* - L_f^*$) and the gender wage gap ($w_m^* - w_f^*$) of the status quo (the equilibrium in figure 6) as well as in four different counterfactuals that eliminate one-by-one: 1) paternalistic discrimination ($\alpha_f \mathcal{W}_f^E = \alpha_m \mathcal{W}_m^E$), 2) taste-based discrimination ($d = 0$), 3) statistical discrimination ($\Pi_f^E = \Pi_m^E$), and 4) differences in labor supply ($L_f^S = L_m^S$).

6.3.3 Counterfactual Policy Interventions

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

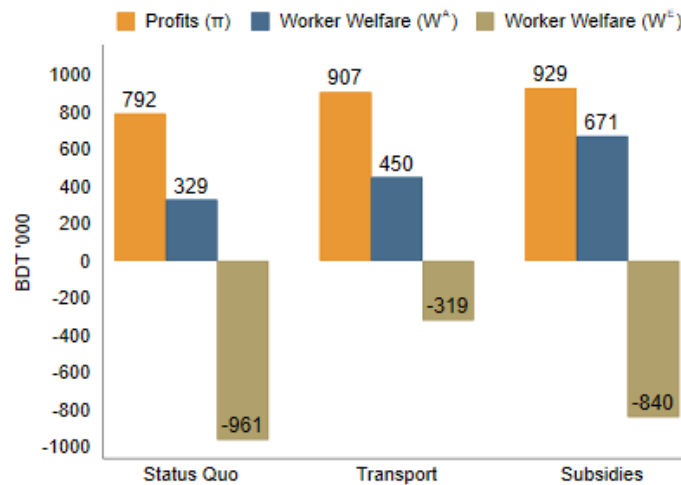
Safe Transport for Female Workers We estimate the welfare effects and financial cost of providing safe transport to female workers at a cost to the policymaker of BDT 800 (USD 8) for each woman hired. This expense reflects the cost of a private car service in our setting.

Female Subsidy We estimate the effects of providing employers a subsidy s for each women hired. The labor supply at each wage w^E is given by all female workers willing to work at the

wage $w^A = w^E + s$. The labor demand at each wage w^E is given by employers' demand for workers willing to work at wage w^A when paying wage w^E . The equilibrium wage equalizes supply and demand. We calculate the subsidy that equalizes the policymaker's expenditures of the transport and subsidy interventions, amounting to BDT 900 (USD 9) per woman hired.⁵⁶

Results Both the transport and subsidy interventions increase employer profits and worker welfare. Transport is more effective than hiring subsidies at reducing the gender employment gap (−78% versus −61%) but less effective at reducing the gender wage gap (BDT −292, USD −3, versus BDT −663, USD −7, appendix table C.15). The transport results in smaller increases in profits (BDT 115k, USD 1,150, versus BDT 137k, USD 1,370) and worker welfare using applicants' perception of welfare (BDT 121k, USD 1,210, versus BDT 342k, USD 3,420), but larger increases in worker welfare using employers' perception of welfare (BDT 642k, USD 6,420, versus BDT 122k, USD 1,220, figure 8). The increases in profits and worker welfare from the transport outweigh the implementation costs under employers' perception but not applicants' perception of welfare, while the increases in profits and worker welfare from the subsidies outweigh the implementation costs under applicants' but not employers' perception of welfare.⁵⁷

Figure 8: Welfare Effects of Transport and Subsidy Interventions



Notes: The figure shows total profits and total worker welfare (male + female worker welfare) using applicants' perceptions of worker welfare (W^A) and employers' perceptions of worker welfare (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 900 (USD 9). Results in BDT '000.

While subsidies have larger benefits than transport in terms of reducing the gender wage gaps and increasing employer profits, the relative effects on worker welfare—and thus total

⁵⁶ The expense per female worker is higher under the subsidy policy as fewer women get hired than under the transport policy.

⁵⁷ Forcing employers to provide the transport themselves increases both the gender employment and wage gaps and reduces profits (appendix table C.15). It increases worker welfare only using employers' perception of welfare.

welfare—depend on whether employers or applicants have more accurate beliefs about worker welfare. Assuming that true experienced worker welfare is a convex combination of employers’ and applicants’ perception of worker welfare, $\mathcal{W}_g = \lambda \mathcal{W}_g^E + (1 - \lambda) \mathcal{W}_g^A$, and summing the total worker welfare of male and female workers, employer profits, and costs to the implementers, the transport intervention increases welfare more when $\lambda \geq 0.30$. For example, transport improves welfare more when applicants underestimate the job costs, while subsidies enhance welfare more when employers overestimate the job costs due to low worker-specific job costs.

7 Conclusion

This paper considers paternalism as a source of labor market discrimination. Combining a labor market model with data from two parallel field experiments, we document a high degree of paternalistic discrimination. An equilibrium model predicts that eliminating paternalistic discrimination reduces the gender employment gap by 24% and the gender wage gap by BDT 209 (USD 2) in our experimental setting.

We believe that the magnitude of paternalism in our setting is likely similar to other settings in which safety is a salient factor. However, in more natural settings, employers directly interact with workers, which may increase paternalism if employers feel a greater responsibility for their workers or decrease paternalism if employers update their beliefs about job costs to workers. In addition, paternalism is likely a larger factor in hiring in settings where the information gap between employers and applicants is large. We discuss the external relevance of our findings in appendix B.8.

Studying paternalistic discrimination offers valuable insights for policymakers aiming to affect labor market outcomes. For one, decreasing workers’ job costs, both in the workplace or during the commute, or increasing workers’ benefits may induce increases in both the supply of and demand for labor. Meanwhile, programs targeting supply-side changes—such as increasing women’s qualifications in the workforce—may not translate into additional hiring if they fail to address demand-side constraints. Fundamentally, paternalistic discrimination is driven by the perception that one group faces larger costs from employment than another. If minority status in the workforce or in society itself generates costs to minorities, paternalistic discrimination may lead to a “minority trap” (Shan, 2022). That is, a disadvantaged group may not be hired because of the very costs related to being disadvantaged, reinforcing the disadvantaged status.⁵⁸

Future research should examine the long-run dynamics of paternalistic discrimination, for both firms and workers. Under what conditions can paternalistic firms remain in business? To what extent does paternalism affect women’s career trajectories or preferences, thus contributing to systemic discrimination? Our data suggest that those who suffer the most from

⁵⁸ For example, employers may not hire minority workers if they believe that they will suffer ostracism.

paternalistic discrimination are women with little experience. Obstacles to early-career employment may keep these applicants off the career ladder, slowing human capital accumulation and eliminating some future opportunities. While we focus on hiring decisions, other-regarding preferences may also lead to differential treatment in task assignment, promotion, or layoff decisions. Moreover, paternalistic discrimination might occur not only in the labor market but also inside the household (towards daughters) or in school (towards female students), thus differentially shaping the preferences of girls and boys during their most formative stages. Understanding these issues can enhance our understanding of gender differences in and outside the labor market and our analysis of available policies.

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A Theory Appendix

A.1 Production Function

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

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

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

A.2 Derivation of Prediction 1

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

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

$$\frac{\partial \mathcal{W}_{kg}}{\partial c_g} = -\frac{\partial}{\partial c_g} \mathbb{E}_k[u_{ki}(c_g + c_i + c_{kg}) \mid \mathbb{E}_i[u_i^{E:A}(c_g + c_i + c_{kg})] \leq w_g], \quad (8)$$

for $u_{ki} \in \{u_{ki}^E, u_i^{E:A}\}$.

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

fixed going forward, i.e., that $\frac{\partial \mathcal{W}_{kg}}{\partial c_g} < 0$ and equal to the direct effect.

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

$$\begin{aligned} FOC_{L_{kf}} \quad d_{kf} + \frac{\partial Y^E(L_{kf}, L_{km})}{\partial L_{kf}} + \alpha_{kf} \mathcal{W}_{kf} - w_f &= 0 \\ FOC_{L_{km}} \quad d_{km} + \frac{\partial Y^E(L_{kf}, L_{km})}{\partial L_{km}} + \alpha_{km} \mathcal{W}_{km} - w_m &= 0. \end{aligned} \quad (9)$$

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

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

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

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

A.3 Derivation of Prediction 2

Prediction 2 states that holding selection and productivity constant, the labor demand of deferential employers is increasing weakly more in subsidies to workers than in equally (or lower) priced worker amenities.

To see this, consider a worker who does not receive a given amenity as part of her job. If the amenity is sufficiently valuable and within the worker's budget, the worker will purchase the amenity. As a result, the worker is at least as well off with a bonus payment that allows her to purchase the amenity than with receiving the amenity directly. That is, an in-kind amenity is (weakly) less valuable than a cost-equivalent bonus payment.

Knowing this, a deferential employer understands that a subsidy to women is at least as valuable to female workers as a ride home, as long as the value of the subsidy exceeds the cost of the ride. Thus, a deferential employer's other-regarding utility is larger from hiring a worker who has the option to either purchase the amenity or keep the extra cash compared to hiring a worker who can only receive the amenity.

A.4 Derivation of Prediction 3

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

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

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

for $u_{ki} \in \{u_{ki}^E, u_i^{E:A}\}$.

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

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

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

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

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

A.5 Derivation of Prediction 4

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

A.6 Derivation of Prediction 5

We derive prediction 5 in four steps. First, we derive how labor demand for men is changing in female-specific costs and wages. Second, we set up the system of equations describing the equilibrium. Third, we show that this system of equations has a solution. Fourth, we show how the equilibrium labor quantity and wages respond to changes in gender-specific costs c_g .

First, to assess under which conditions male and female workers are substitutes, complements, or neither, we calculate the cross-wage elasticity of demand of male labor with respect to female wages. Male and female workers are substitutes if the cross-wage elasticity is positive, i.e., an increase in female wages increases the demand for male workers, complements if the cross-wage elasticity is negative, i.e., an increase in female wages decreases the demand for male workers, and neither substitutes nor complements if the cross-wage elasticity is 0.

$$\epsilon_{w_f, w_m} = \frac{w_f}{L_{km}} \frac{\partial L_{km}}{\partial w_f} = - \underbrace{\frac{w_f}{L_{km}}}_{<0} \underbrace{\frac{\frac{\partial^2 Y^E}{\partial L_{km} \partial L_{kf}} (1 - \alpha_{kf})}{\frac{\partial^2 Y^E}{\partial L_{kf}^2} \frac{\partial^2 Y^E}{\partial L_{km}^2} - \left(\frac{\partial^2 Y^E}{\partial L_{km} \partial L_{kf}} \right)^2}}_{>0} \quad (13)$$

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 $\frac{\partial^2 Y^E}{\partial L_{km} \partial L_{kf}} = 0$. That is, male and female workers are substitutes if and only if $\frac{\partial^2 Y^E}{\partial L_{km} \partial L_{kf}} < 0$, complements if and only if $\frac{\partial^2 Y^E}{\partial L_{km} \partial L_{kf}} > 0$, and neither substitutes nor complements if and only if $\frac{\partial^2 Y^E}{\partial L_{km} \partial L_{kf}} = 0$.

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

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

opposite gender.

$$\frac{\partial L_{km}}{\partial c_f} = \frac{\alpha_{kf} \overbrace{\frac{\partial \mathcal{W}_{kf}}{\partial c_f}}^{<0} \overbrace{\frac{\partial^2 Y^E}{\partial L_{km} \partial L_{kf}}}^{?}}{\underbrace{\frac{\partial^2 Y^E}{\partial L_{kf}^2} \frac{\partial^2 Y^E}{\partial L_{km}^2} - \left(\frac{\partial^2 Y^E}{\partial L_{km} \partial L_{kf}} \right)^2}_{>0}}. \quad (14)$$

Assuming $\alpha_{kf} \geq 0$, the above is 0 if $\alpha_{kf} = 0$ or if $Y_{L_{km}, L_{kf}}^E = 0$, i.e., male and female workers are neither substitutes nor complements. For $\alpha_{kf} > 0$, it is < 0 if $Y_{L_{km}, L_{kf}}^E > 0$, i.e., male and female workers are complements, and > 0 if $Y_{L_{km}, L_{kf}}^E < 0$, 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. Note that the change in male hiring is increasing in α_{kf} .

Note from equation 10 that an increase in costs has the smallest effect on demand for female labor when male and female labor are neither substitutes nor complements. Intuitively, if male and female labor are substitutes, employers substitute towards male labor when the perceived costs to female labor increase. On the other hand, if male and female labor are complements, the demand for male labor decreases, further reducing the demand for female labor.

Second, we set up the system of equations describing the equilibrium.

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

$$L_g = L_g^S \equiv \int_i \mathbb{1} \left(\mathbb{E}_i[u^A(c_i + c_{kg} + c_g)] \leq w_g \right) h_g^I(c_i) dc_i \quad (15)$$

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:

$$L_g = L_g^D \equiv \int_k \left(\frac{\partial Y^E(w_g - d_{kg} - \alpha_{kg} \mathcal{W}_{kg}, L_{kg'})}{\partial L_{kg}} \right)^{-1} dk, \quad (16)$$

where g' is the opposite gender.

The system of equations given by 16 and 15 then describes the equilibrium.

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

$$\begin{bmatrix} 1 & 0 & -\frac{\partial L_f^S}{\partial w_f} & 0 \\ 0 & 1 & 0 & -\frac{\partial L_m^S}{\partial w_m} \\ 1 & 0 & -\frac{\partial L_f^D}{\partial w_f} & -\frac{\partial L_f^D}{\partial w_m} \\ 0 & 1 & -\frac{\partial L_m^D}{\partial w_f} & -\frac{\partial L_m^D}{\partial w_m} \end{bmatrix} \begin{bmatrix} \frac{\partial L_f^*}{\partial c_f} \\ \frac{\partial L_m^*}{\partial c_f} \\ \frac{\partial w_f^*}{\partial c_f} \\ \frac{\partial w_m^*}{\partial c_f} \end{bmatrix} = \begin{bmatrix} \frac{\partial L_f^S}{\partial c_f} \\ 0 \\ \frac{\partial L_f^D}{\partial c_f} \\ \frac{\partial L_m^D}{\partial c_f} \end{bmatrix} \quad (17)$$

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

$$\begin{aligned} \frac{\partial L_f^*}{\partial c_f} &= \frac{|J_1|}{|J|} & \frac{\partial L_m^*}{\partial c_f} &= \frac{|J_2|}{|J|} \\ \frac{\partial w_f^*}{\partial c_f} &= \frac{|J_3|}{|J|} & \frac{\partial w_m^*}{\partial c_f} &= \frac{|J_4|}{|J|}. \end{aligned}$$

Here $|J_j|$ is the matrix resulting from replacing the j th column of the Jacobian matrix with the solution to the system of equations. As we already know that $|J| > 0$, we only have to 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:

$$|J_1| = \underbrace{\frac{\partial L_f^S}{\partial c_f}}_{<0} \left(\underbrace{\frac{\partial L_f^D}{\partial w_f} \frac{\partial L_m^D}{\partial w_m}}_{(1-\alpha_{kf})(1-\alpha_{km})>0} - \underbrace{\frac{\partial L_f^D}{\partial w_m} \frac{\partial L_m^D}{\partial w_f}}_{>0} - \underbrace{\frac{\partial L_f^D}{\partial w_f} \frac{\partial L_m^S}{\partial w_m}}_{>0} \right) - \underbrace{\frac{\partial L_f^S}{\partial w_f}}_{<0} \left(\underbrace{\frac{\partial L_f^D}{\partial c_f} \frac{\partial L_m^D}{\partial w_m}}_{-(1-\alpha_{km})\alpha_{kf} \frac{\partial w_f}{\partial c_f} > 0} - \underbrace{\frac{\partial L_f^D}{\partial w_m} \frac{\partial L_m^D}{\partial c_f}}_{>0} - \underbrace{\frac{\partial L_f^D}{\partial c_f} \frac{\partial L_m^S}{\partial w_m}}_{>0} \right) < 0 \quad (18)$$

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

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

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

$$|J_3| = \underbrace{\frac{\partial L_f^D}{\partial w_m} \frac{\partial L_m^D}{\partial c_f}}_{>0} + \underbrace{\left(\frac{\partial L_m^D}{\partial w_m} - \frac{\partial L_m^S}{\partial w_m} \right)}_{<0} \underbrace{\left(\frac{\partial L_f^S}{\partial c_f} - \frac{\partial L_f^D}{\partial c_f} \right)}_{?} \quad (19)$$

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 19, we find that equilibrium wages *decrease* if and only if:

$$\left| \frac{\partial L_f^S}{\partial c_f} \right| < \delta \left| \frac{\partial L_f^D}{\partial c_f} \right|. \quad (20)$$

Here,

$$\delta \equiv 1 - \frac{r_{w_m}^D r_{c_f}^D}{1 - r_{w_m}} \in (0, 1]$$

This implies that equilibrium wages decrease if the labor demand shift is proportionally

larger than the labor supply shift. The ratios $r_{w_m}^D$ and $r_{c_f}^D$ estimate how much the labor demand responds to changes in the wages or costs of the other gender relative to the labor demand responds to changes in the wages or costs 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 male and female labor are either substitutes or complements. Given assumption 4 and substituting from equations 10, 12, 13 and 14, $r_{w_m}^D r_{c_f}^D < 1$.

If male and female labor are neither substitutes nor complements, in which case $\delta = 1$, then the equilibrium wage decreases whenever the demand elasticity in costs is larger than the supply elasticity in costs.

δ is increasing in r_{w_m} , the magnitude of the ratio of the supply and demand elasticities with respect to male wages. Intuitively, if an increase in the wage for male labor increases male labor supply by a relatively large amount, employers will be able to replace female labor with male labor without having to pay drastically higher wages for all of their male labor. This makes substituting more attractive, which puts downward pressure on female wages.

δ is decreasing in the relative curvature of the production function across versus within gender. We consider the two cases of female and male workers being substitutes or complements:

- Complements, $Y_{L_f L_m}^E > 0$: An increase in gender-specific costs for female labor reduces the female labor hired and the marginal productivity of male labor. Intuitively, the higher the complementarity between men and women, the larger the positive impact of each woman on the productivity of male workers. As men and women are strong complements, this, in turn, increases the demand for female workers and puts upward pressure on female equilibrium wages.
- Substitutes, $Y_{L_f L_m}^E < 0$: An increase in gender-specific costs for female labor reduces the female labor hired and increases the marginal productivity of male labor.

A.7 Prediction 6

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

Prediction 6 (Substitutability). *Holding selection and productivity constant, the demand for labor of the opposite gender and wages of labor of the opposite gender are increasing in*

gender-specific costs to substitute labor and decreasing in gender-specific costs to complement labor.

Proof We have shown in equations 13 and 14 that labor demand for labor of the opposite gender 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:

$$|J_2| = \underbrace{\frac{\partial L_m^S}{\partial w_m}}_{>0} \left(\underbrace{\frac{\partial L_m^D}{\partial c_f}}_{?} \underbrace{\frac{\partial L_f^S}{\partial w_f}}_{+} - \underbrace{\frac{\partial L_m^D}{\partial w_f}}_{?} \underbrace{\frac{\partial L_f^S}{\partial c_f}}_{-} \right) \quad (21)$$

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 workers. $\frac{\partial L_m^*}{\partial c_f} = 0$ iff male and female workers are unrelated, $\frac{\partial L_m^*}{\partial c_f} > 0$ iff male and female workers are substitutes and $\frac{\partial L_m^*}{\partial c_f} < 0$ iff male and female workers are complements. This is true for any $\alpha_f \in [0, 1]$.

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

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

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

$$|J_4| = \underbrace{\frac{\partial L_m^D}{\partial c_f}}_{?} \underbrace{\frac{\partial L_f^S}{\partial w_f}}_{+} - \underbrace{\frac{\partial L_m^D}{\partial w_f}}_{?} \underbrace{\frac{\partial L_f^S}{\partial c_f}}_{-} \quad (22)$$

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

A.8 Welfare Effects of Other-Regarding Employer Preferences

We consider under which conditions other-regarding preferences are welfare-reducing and under which they are welfare-enhancing. For tractability, we make functional form assumptions for $u^E(\cdot)$, $u^A(\cdot)$ and $u^{E:A}(\cdot)$: We assume that utility is linear in costs c_{igk} .

A.8.1 Share of Applicant–Employer Encounters that are Welfare-Reducing

Other-regarding employer preferences reduce welfare in a random employer–applicant encounter if and only if the following three conditions are met:

1. Applicants with negative welfare who get hired with other-regarding preferences but not without, which implies that the following three conditions are satisfied:

- (a) The worker does not get hired without other-regarding preferences:

$$d_{kg} + Y^E - w_g < 0.$$

- (b) The worker gets hired with other-regarding preferences:

$$d_{kg} + Y^E - w_g + \alpha_{kg}(w_g - c_g - E_k[c_i|w_g - c_g - c_i - E_i[c_{kg}] \geq 0] - c_{kg}) \geq 0.$$

- (c) The experienced welfare is negative:

$$w_g - c_g - c_i - c_{kg} < 0.$$

The set of employers for whom conditions (a) and (b) are true consists of those for whom c_{kg} is smaller than some cutoff c_{kg}^* :

$$c_{kg} < c_{kg}^* = w_g - c_g - E_k[c_i|w_g - c_g - c_i - \bar{c}_g^K \geq 0]$$

This share of employers is given by the following expression:

$$P(c_{kg} < c_{kg}^*) = H_g^K(w_g - c_g - E_k[c_i|w_g - c_g - c_i - \bar{c}_g^K \geq 0]).$$

The set of applicants for whom condition (c) is true, conditional on a level of c_{kg} , consists of those for whom c_i is greater than some cutoff c_i^* :

$$c_i > c_i^*(c_{kg}) = w_g - c_g - c_{kg}.$$

This share of applicants is given by the following expression:

$$P(c_i > c_i^*(c_{kg})) = 1 - H^I(w_g - c_g - c_{kg}).$$

2. Applicants with positive welfare who get hired without other-regarding preferences but not with, which implies that the following three conditions are satisfied:

- (a) The worker gets hired without other-regarding preferences:

$$d_{kg} + Y^E - w_g \geq 0.$$

- (b) The worker does not get hired with other-regarding preferences:

$$d_{kg} + Y^E - w_g + \alpha_{kg}(w_g - c_g - E_k[c_i|w_g - c_g - c_i - E_i[c_{kg}] \geq 0] - c_{kg}) < 0.$$

- (c) The experienced welfare is positive:

$$w_g - c_g - c_i - c_{kg} \geq 0.$$

The set of employers for whom conditions (a) and (b) are true consists of those for whom c_{kg} is larger than c_{kg}^* :

$$c_{kg} > c_{kg}^* = w_g - c_g - E_k[c_i | w_g - c_g - c_i - \bar{c}_g^K \geq 0]$$

This share of employers is given by the following expression:

$$P(c_{kg} > c_{kg}^*) = 1 - H_g^K(w_g - c_g - E_k[c_i | w_g - c_g - c_i - \bar{c}_g^K \geq 0]).$$

The set of applicants for whom condition (c) is true, conditional on a level of c_{kg} , consists of those for whom c_i is smaller than some cutoff c_i^* :

$$c_i \leq c_i^*(c_{kg}) = w_g - c_g - c_{kg}.$$

This share of applicants is given by the following expression:

$$P(c_i \leq c_i^*(c_{kg})) = H^I(w_g - c_g - c_{kg}).$$

Thus, the total probability of an encounter between an applicant and an other-regarding employer to be welfare-reducing is given by the following expression:

$$\left(P(c_{kg} < c_{kg}^*) \int_{c_{kg} < c_{kg}^*} P(c_i > c_i^*(c_{kg})) dc_i \right) + \left(P(c_{kg} > c_{kg}^*) \int_{c_{kg} > c_{kg}^*} P(c_i \leq c_i^*(c_{kg})) dc_i \right).$$

The share of encounters that are welfare-enhancing is given by the following expression:

$$\left(P(c_{kg} > c_{kg}^*) \int_{c_{kg} > c_{kg}^*} P(c_i > c_i^*(c_{kg})) dc_i \right) + \left(P(c_{kg} < c_{kg}^*) \int_{c_{kg} < c_{kg}^*} P(c_i \leq c_i^*(c_{kg})) dc_i \right).$$

A.8.2 Share of Applicant–Employer Encounters that are Welfare-Enhancing

Other-regarding employer preferences increase welfare in a random employer–applicant encounter if and only if:

1. Applicants with negative welfare who get hired without other-regarding preferences but not with:
 - (a) The worker gets hired without other-regarding preferences:
 $d_{kg} + Y^E - w_g \geq 0.$
 - (b) The worker does not get hired with other-regarding preferences:
 $d_{kg} + Y^E - w_g + \alpha_{kg}(w_g - c_g - E_k[c_i | c_i \leq w_g - c_g - \bar{c}_g^K] - c_{kg}) < 0$
 - (c) The experienced welfare is negative:
 $w_g - c_g - c_i - c_{kg} < 0.$

2. Applicants with positive welfare who get hired with other-regarding preferences but not without:

(a) The worker gets hired with other-regarding preferences:

$$d_{kg} + Y^E - w_g + \alpha_{kg}(w_g - c_g - E_k[c_i | c_i \leq w_g - c_g - \bar{c}_g^K] - c_{kg}) \geq 0.$$

(b) The worker does not get hired without other-regarding preferences:

$$d_{kg} + Y^E - w_g < 0.$$

(c) The experienced welfare is positive:

$$w_g - c_g - c_i - c_{gk} \geq 0.$$

The share of encounters that are welfare-enhancing is given by the following expression:

$$\left(P(c_{kg} > c_{kg}^*) \int_{c_{kg} > c_{kg}^*} P(c_i > c_i^*(c_{kg})) dc_i \right) + \left(P(c_{kg} < c_{kg}^*) \int_{c_{kg} < c_{kg}^*} P(c_i \leq c_i^*(c_{kg})) dc_i \right).$$

A.9 Example with CES Production Function

The production function of employers in industry j is:

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

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, v is the degree of homogeneity of the production function (where $v = 1$ is constant returns to scale, $v < 1$ is decreasing returns to scale, and $v > 1$ 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:

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

Rearranging, we can solve for the labor g demand:

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

B Technical Appendix

B.1 Ethical Considerations

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

B.2 Information about Sample Industries

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

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

B.3 Field Setup

Figure C.1: Applicant Recruitment Setup



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

Figure C.2: Night-Shift Workshop and Job

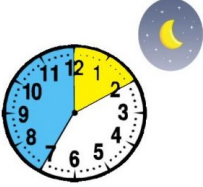



Notes: The picture shows one of our night-shift workshops.

B.4 Experimental Interfaces





B.4.1 Hiring Experiment

Figure C.3: Experimental Interface to Make Productivity Predictions

Shift time	
	
	
Niloy Unmarried Passed Honors 1st year Less than 1 year of experience Excel Score: 35%	
What is the likelihood (0-100) the applicant shows up and completes the shift?	<input type="text"/>
Given that the applicant showed up, what percentage (out of 100%) of tasks on the job do you think the applicant will complete?	<input type="text"/>
Given that the applicant showed up, what do you think the applicant Excel test score will be, on a final assessment test measuring the workers' final Excel ability after completing the workshop out of 100?	<input type="text"/>

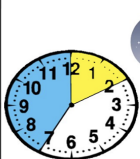



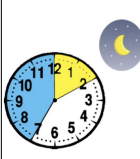








Notes: Translated from Bangla to English.

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

Shift time	Transport facility
	
	
<p>Candidate Profile:</p> <p>Riyaj Unmarried Passed Honors 1st year Less than 1 year of experience Excel Score: 35%</p> <p>How useful do you think it is to participate in the job for five hours for Riyaj in terms of the skills they will acquire as well as future career opportunities on a scale of 0 (not useful at all) to 10 (extremely useful)? Please answer using this scale below.</p> <div style="text-align: center;"> 0 1 2 3 4 5 6 7 8 9 10 </div> <p>How useful do you think is this job for Riyaj</p>	<p>Candidate Profile:</p> <p>Khairun Unmarried Passed Honors 2nd year Less than 1 year of experience Excel Score: 40%</p> <p>How useful do you think it is to participate in the job for five hours for Khairun in terms of the skills they will acquire as well as future career opportunities on a scale of 0 (not useful at all) to 10 (extremely useful)? Please answer using this scale below.</p> <div style="text-align: center;"> 0 1 2 3 4 5 6 7 8 9 10 </div> <p>How useful do you think is this job for Khairun</p>
<p>How dangerous, unpleasant or socially unacceptable do you think this job is for Riyaj, including their commute from and to their home, with 0 indicating a very safe job, equivalent to working from home and 10 indicating that the job is very dangerous or very unpleasant or very socially unacceptable.</p> <div style="display: flex; justify-content: space-between; font-size: small;"> Not dangerous, not unpleasant or not socially unacceptable Very dangerous, very unpleasant or very socially unacceptable </div> <div style="text-align: center;"> 0 1 2 3 4 5 6 7 8 9 10 </div> <p>Scale</p>	<p>How dangerous, unpleasant or socially unacceptable do you think this job is for Khairun, including their commute from and to their home, with 0 indicating a very safe job, equivalent to working from home and 10 indicating that the job is very dangerous or very unpleasant or very socially unacceptable.</p> <div style="display: flex; justify-content: space-between; font-size: small;"> Not dangerous, not unpleasant or not socially unacceptable Very dangerous, very unpleasant or very socially unacceptable </div> <div style="text-align: center;"> 0 1 2 3 4 5 6 7 8 9 10 </div> <p>Scale</p>
<p>I will now ask you what you think should be the minimum wage Riyaj should accept the job for.</p> <p>Some reminders for answering this question:</p> <ul style="list-style-type: none"> Based on your beliefs about the candidate's performance on the final test and the promotion rates of men, you previously said the candidate's likelihood of promotion is 20%. Keep in mind the usefulness of the job as well as how dangerous, unpleasant or socially unacceptable you think this job is for Riyaj. <p>What do you think should be the minimum wage at which Riyaj should accept this job with the benefits we mentioned? Meaning they should not do the job for less than this amount as it would not fairly compensate them.</p> <div style="border: 1px solid black; height: 20px; width: 100%;"></div>	<p>I will now ask you what you think should be the minimum wage Khairun should accept the job for.</p> <p>Some reminders for answering this question:</p> <ul style="list-style-type: none"> We will provide hired candidates with a safe private transport with accompanying supervisors to ensure all workers reach home safely and without problems. We are providing this as a job benefit Based on your beliefs about the candidate's performance on the final test and the promotion rates of women, you previously said the candidate's likelihood of promotion is 0%. Keep in mind the usefulness of the job as well as how dangerous, unpleasant or socially unacceptable you think this job is for Khairun. <p>What do you think should be the minimum wage at which Khairun should accept this job with the benefits we mentioned? Meaning they should not do the job for less than this amount as it would not fairly compensate them.</p> <div style="border: 1px solid black; height: 20px; width: 100%;"></div>

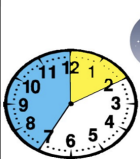




Notes: Translated from Bangla to English.

Figure C.5: Experimental Interface to Make Hiring Decisions. Left: No Transport + Male Employer Subsidy, Right: Transport + Male Worker Subsidy

Shift time	Recruited candidate's payment	Employer's payment	Shift time	Transport facility	Recruited candidate's payment	Employer's payment
	  <div style="display: flex; justify-content: space-around;"> 1500 + 0 1500 + 0 </div>	<div style="display: flex; justify-content: space-around;"> <div style="border: 1px solid black; padding: 5px;">500 + 1000</div> <div style="border: 1px solid black; padding: 5px;">500 + 0</div> </div> 			  <div style="display: flex; justify-content: space-around;"> 1500 + 1000 1500 + 0 </div>	<div style="display: flex; justify-content: space-around;"> <div style="border: 1px solid black; padding: 5px;">500 + 0</div> <div style="border: 1px solid black; padding: 5px;">500 + 0</div> </div> 
Do you want to hire Shimu or Faroque for the job?			Do you want to hire Mahfuz or Sumona for the job?			
						
<div style="display: flex; justify-content: space-between;"> <div style="width: 45%;"> Shimu Unmarried <input type="radio"/> Passed HSC/Equivalent 1 to 3 years of experience Excel Score: 25% </div> <div style="width: 45%;"> Faroque Unmarried <input type="radio"/> Passed Honors 2nd year <1 year of experience Excel Score: 35% </div> </div>			<div style="display: flex; justify-content: space-between;"> <div style="width: 45%;"> Mahfuz Married with children <input type="radio"/> Passed SSC/Equivalent 3 years of experience Excel Score: 20% </div> <div style="width: 45%;"> Sumona Unmarried <input type="radio"/> Passed Honors 4th year <1 year of experience Excel Score: 15% </div> </div>			

Notes: Translated from Bangla to English.

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

Shift time	Recruited candidate's payment	Employer's payment	Shift time	Transport facility	Recruited candidate's payment	Employer's payment
	<div style="font-size: 2em; font-weight: bold; display: flex; justify-content: space-around;"> 1 2 </div> <div style="display: flex; justify-content: space-around;"> 1500 + 0 1500 + 0 </div>	<div style="display: flex; justify-content: space-around;"> <div style="border: 1px solid black; padding: 5px;">500 + 1000</div> <div style="border: 1px solid black; padding: 5px;">500 + 0</div> </div> 			<div style="font-size: 2em; font-weight: bold; display: flex; justify-content: space-around;"> 1 2 </div> <div style="display: flex; justify-content: space-around;"> 1500 + 1000 1500 + 0 </div>	<div style="display: flex; justify-content: space-around;"> <div style="border: 1px solid black; padding: 5px;">500 + 0</div> <div style="border: 1px solid black; padding: 5px;">500 + 0</div> </div> 
Do you want to hire Taniya or Ridhoy for the job?			Do you want to hire Sayed or Nishat for the job?			
<div style="font-size: 2em; font-weight: bold;">1</div>	<div style="font-size: 2em; font-weight: bold;">2</div>		<div style="font-size: 2em; font-weight: bold;">1</div>	<div style="font-size: 2em; font-weight: bold;">2</div>		
<div style="display: flex; justify-content: space-between;"> <div style="width: 45%;"> Taniya Female <input type="radio"/> Unmarried Passed Class 10 <1 year of experience Excel Score: 25% </div> <div style="width: 45%;"> Ridhoy Male <input type="radio"/> Unmarried Passed Honors 2nd year 1 to 3 years of experience Excel Score: 35% </div> </div>			<div style="display: flex; justify-content: space-between;"> <div style="width: 45%;"> Sayed Male <input type="radio"/> Unmarried Passed HSC 2nd year <1 year of experience Excel Score: 15% </div> <div style="width: 45%;"> Nishat Female <input type="radio"/> Unmarried Passed Honors 2nd year 1 to 3 years of experience Excel Score: 20% </div> </div>			

Notes: Translated from Bangla to English.

B.4.2 Application Experiment

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

Shift time		10% of applicants will be promoted	Shift time		Transport facility	10% of applicants will be promoted
Wage and amenities		Basic Wage Switching Point	Wage and amenities		Basic Wage Switching Point	
Basic wage 100 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 100 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 250 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 250 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 500 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 500 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 750 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 750 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 1000 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 1000 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 1250 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 1250 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 1500 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 1500 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 1750 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 1750 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 2000 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 2000 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 2250 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 2250 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 2500 Taka 10% of applicants will be promoted		<input checked="" type="radio"/>	Basic wage 2500 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input checked="" type="radio"/>	
Basic wage 2750 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 2750 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 3000 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 3000 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 3250 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 3250 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 3500 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 3500 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 3750 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 3750 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 4000 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 4000 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 4250 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 4250 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 4500 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 4500 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 4750 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 4750 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	
Basic wage 5000 Taka 10% of applicants will be promoted		<input type="radio"/>	Basic wage 5000 Taka Will be dropped home in office transport 10% of applicants will be promoted		<input type="radio"/>	

Notes: Translated from Bangla to English.

B.5 Matching of Applicant Pairs in the Hiring Experiment

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

B.6 Survey Questions

B.6.1 Understanding Questions in the Hiring Experiment

1. What's the timing of the Excel workshop and job? a) 9 a.m.to 5 p.m.. b) 7 p.m. to 12 a.m.. c) 9 p.m. to 5 a.m..
2. *Transport*: When will the recruited workers learn about the safe transport? a) Before the shift. b) At the end of the shift. *No Transport*: When do workers learn that the Excel workshop and job takes place from 7 p.m. to 12 a.m.? a) They already learned when they applied for the job. b) Before the shift. c) At the end of the shift.
3. How much compensation do you receive per task your recruited worker completes? a) 3 Taka. b) 4 Taka. c) 5 Taka.
4. Based on the lottery, what is the bonus payment that you are going to receive? a) 0 Taka. b) 1,000 Taka if the recruited worker is male. c) 1,000 Taka if the recruited worker is female.
5. Based on the lottery, what is the bonus payment that the recruited worker will receive? a) 0 Taka. b) 1,000 Taka if the recruited worker is male. c) 1,000 Taka if the recruited worker is female.

B.6.2 Understanding Questions in the Application Experiment

1. What's the timing of the Excel workshop and job? a) 9 a.m.to 5 p.m.. b) 7 p.m. to 12 a.m.. c) 9 p.m. to 5 a.m..
2. For the job and amenities that you are eligible for, which of the following is true? a) Most applicants do not receive a promotion premium and a promotion certificate. b) Most applicants receive a promotion premium and a promotion certificate. c) Some applicants will receive a promotion premium, and other applicants will receive a promotion certificate.

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

B.7 Structural Estimation

B.7.1 Calculating the Cost Conversion Rate

First, we estimate equation 3 replacing the *No Transport* indicator with the predicted costs for the female and male workers compared in each pair. 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 the costs of the other applicant fixed. 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' evaluation of a one-Likert scale increase in terms of BDT paid to the worker.

B.7.2 Maximum Likelihood

To estimate the McFadden's conditional logit model, we maximize the log-likelihood function given our data (McFadden, 1974).

The likelihood function is

$$\mathcal{L}(d, \beta, \alpha_f, \alpha_m) = \prod_k \prod_i (P_{ki})^{H_{ki}}, \quad (23)$$

where H_{ki} is an indicator that is 1 if employer k hires applicant i over i' .

Taking the log of equation 23, we get the log-likelihood function:

$$\log \mathcal{L}(d, \beta, \alpha_f, \alpha_m) = \sum_k \sum_i H_{ki} \ln(P_{ki}).$$

B.7.3 Control Function Approach

We would like to estimate the following equation:

$$v_{ki} + \varepsilon_{ki} = d_j + \beta_j \Pi_{ki} + \alpha_{jg} \mathcal{W}_{ki} + \varepsilon_{ki}. \quad (24)$$

Assume we do not observe the true profit and welfare beliefs because of measurement error or misreporting. Instead, we observe $\Pi_{ki}^* = \Pi_{ki} + \varepsilon_{ki}^\Pi$ and $\mathcal{W}_{ki}^* = \mathcal{W}_{ki} + \varepsilon_{ki}^\mathcal{W}$ (for example,

employers with high social image concerns might report low profits or welfare whenever they do not hire women in order not to appear sexist). We can thus rewrite equation 24:

$$v_{ki} + \varepsilon_{ki} = d_j + \beta_j \Pi_{ki} + \alpha_{jg} \mathcal{W}_{ki} + \underbrace{\beta_j \varepsilon_{ki}^{\Pi} + \alpha_{jg} \varepsilon_{ki}^{\mathcal{W}}}_{\varepsilon_{ki}^{end}} + \varepsilon_{ki}^{ex}, \quad (25)$$

where ε_{ki}^{end} is potentially correlated with d_j , Π_{ki} and \mathcal{W}_{ki} and ε_{ki}^{ex} 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).⁵⁹ First, let

$$\Pi_{ki} = Z'_k \kappa_j^{\Pi} + X'_i \gamma_j^{\Pi} + \tilde{\varepsilon}_{ki}^{\Pi} \quad (26)$$

and

$$\mathcal{W}_{ki} = Z'_k \kappa_j^{\mathcal{W}} + X'_i \gamma_j^{\mathcal{W}} + \tilde{\varepsilon}_{ki}^{\mathcal{W}}, \quad (27)$$

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_{ki} 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 26 and 27 using OLS separately by industry (and across industries, including industry fixed effects).

Second, we plug the fitted residuals $\hat{\varepsilon}_{ki}^{\Pi}$ and $\hat{\varepsilon}_{ki}^{\mathcal{W}}$ (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 24 and estimate the following logit model:

$$v_{ki} + \varepsilon_{ki} = d_j + \beta_j \Pi_{ki} + \alpha_{jg} \mathcal{W}_{ki} + X_i \gamma + \delta^{\Pi} \hat{\varepsilon}_{ki}^{\Pi} + \delta^{\mathcal{W}} \hat{\varepsilon}_{ki}^{\mathcal{W}} + \tilde{\varepsilon}_{ki}^{ex}, \quad (28)$$

where $\tilde{\varepsilon}_{ki}^{ex} \sim EV1$ is the error term after controlling for the fitted residuals (we also include industry fixed effects if we estimate equation 28 across industries).

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 26 (table C.11). By contrast, the *No Transport* treatment reduces the expected welfare by BDT 641 (USD 6) and BDT 1,672 (USD 16) 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.

The results from equation 28 suggest mismeasurement of reported welfare but not profits ($\hat{\delta}^{\Pi} = 2.1$ $\hat{\delta}^{\mathcal{W}} = -0.4$, table C.12). Controlling for misreporting increases the weight placed

⁵⁹ See also Villas-Boas and Winer (1999), Petrin and Train (2010), Wooldridge (2015) and Hahn and Ridder (2017).

on female welfare.

B.7.4 Random Forest Algorithm

We use a random forest algorithm to predict out-of-sample employer beliefs about profits and welfare. The random forest algorithm avoids over-fitting given our relatively high number of independent variables and low number of observations (Breiman, 2001).⁶⁰ The algorithm operates on the principle of ensemble learning. Initially, N_1 subsets of the data are created by randomly selecting observations with replacement. Subsequently, individual decision trees are constructed for each of the subsets. Here, the random forest algorithm restricts the number of variables considered at each split (N_2) to a randomly selected subset, thereby introducing an additional layer of randomness. The resulting decision trees are then collectively applied to generate predictions. Since we use a regression model, the final predictions are the mean of the predictions across all trees.

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

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

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

B.7.5 Demand Simulation

To estimate demand, we construct a large number (1,000) of simulated employers by using the estimated preferences and calculating the expected value of a male and female hire to

⁶⁰ We use the implementation in Stata by [Schonlau and Zou \(2020\)](#).

each simulated employer at any given wage with and without transport:

$$\widehat{v}_{kg}(w_{jg}, NT_{jg}) = \widehat{d}_j + \widehat{\beta}_j \widehat{\Pi}_{jg}(w_g, NT_{jg}) + \widehat{\alpha}_j \widehat{\mathcal{W}}_{jg}^E(w_{jg}, NT_{jg}). \quad (29)$$

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

$$\widehat{P}_{kg}(w_{jg}, NT_{jg}) = \Pr(\widehat{v}_{kg}(w_{jg}, NT_{jg}) + \Delta\varepsilon_{kg} > 0) = \frac{\exp(\widehat{v}_{kg}(w_{jg}, NT_{jg}))}{1 + \exp(\widehat{v}_{kg}(w_{jg}, NT_{jg}))}, \quad (30)$$

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

$$\widehat{L}_g^D(w_{jg}, NT_{jg}) = \frac{1}{1,000} \sum_k \widehat{P}_{kg}(w_{jg}, NT_{jg}). \quad (31)$$

B.8 Generalizability and External Relevance

We believe paternalistic discrimination may guide decisions in a variety of settings. Following the “SANS” framework of [List \(2020\)](#), we assess the generalizability of our results, considering the selection of participants, attrition from the experiment, the naturalness of the environment, and issues related to scaling.

Selection We recruit real employers with recent hiring experience across a range of industries to hire from a pool of real job seekers. We specifically measure selection into the labor market at different wages to model selection explicitly.

Attrition Workers engage in a one-time, one-shift workshop and job to eliminate concerns about worker attrition within the experiment. In jobs with repeated interactions, attrition can change the composition of employers and workers. For example, employers with other-regarding preferences may go out of business competing against profit-focused firms, reducing paternalistic discrimination. Paternalistic discrimination may also decrease over time if employers learn more about the true costs of the job as they observe hired workers. On the other hand, the market may sustain paternalistic discrimination if employers do not learn over time (e.g., if discrimination is so strong that observations of the discriminated-against group are rare) or if employers develop stronger feelings of responsibility through repeated interaction.

Naturalness To isolate paternalism from other forms of discrimination, we designed our work environment without direct interaction between employer and applicant. We suspect that in natural settings where employers interact directly with workers, employers would feel a greater responsibility for their workers, leading to higher levels of paternalism. Similarly, while we focus on paternalism toward women in the absence of safe transportation at night, we suspect that paternalism is likely to be more prevalent when comparing situations with a larger gap in safety (e.g., hiring on the day shift versus the night shift). Paternalism is likely a larger factor in hiring in settings where the information gap between employers and applicants is large. We believe that the magnitude of paternalism in our setting is likely similar to other settings in which safety is a salient factor. We can only speculate about whether paternalism drives discrimination in other markets (e.g., in developed countries) or with respect to characteristics other than gender (e.g., race, pregnancy, or parental status), but we have no reason to suspect paternalistic discrimination is limited—or even particularly strong—in the development context we study. Discriminatory hiring is likely more muted in markets where differential treatment is banned by law.⁶¹

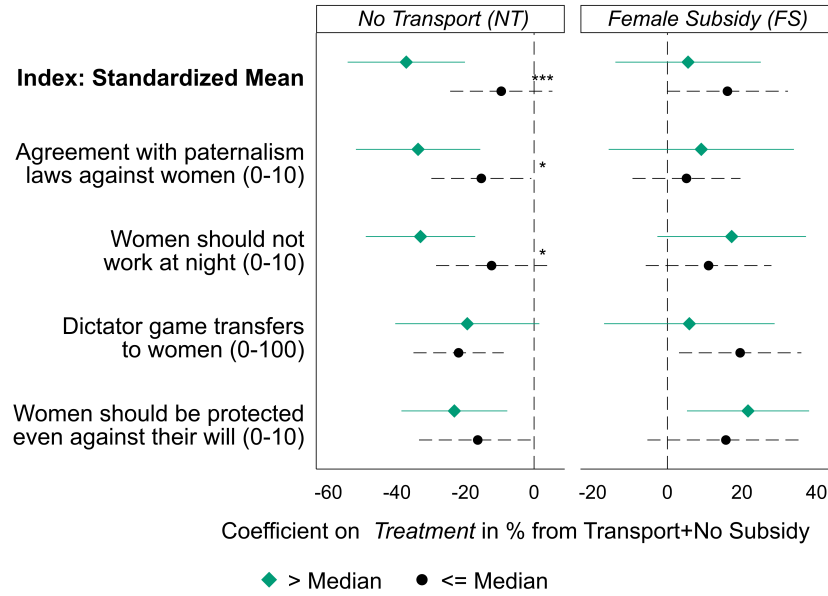
Scaling While scaling a particular intervention is not the primary objective of the study, we estimate the equilibrium effects of offering safe transportation experimentally by observing changes in supply and demand. Large-scale safety measures could lead to long-term changes in supply and demand that we do not capture in our experiment, such as adjustments to traffic patterns and criminal behavior.

⁶¹ However, paternalistic discrimination on the basis of age is sufficiently problematic even in the US to prompt the Equal Employment Opportunity Commission to issue specific guidelines: “The ADEA [Age Discrimination in Employment Act] would prohibit a covered employer from excluding an individual involuntarily from the workplace based on being older, even if the employer acted for benevolent reasons such as protecting the employee due to higher risk of severe illness from COVID-19” (U.S. EEOC, 2022).

C Empirical Appendix

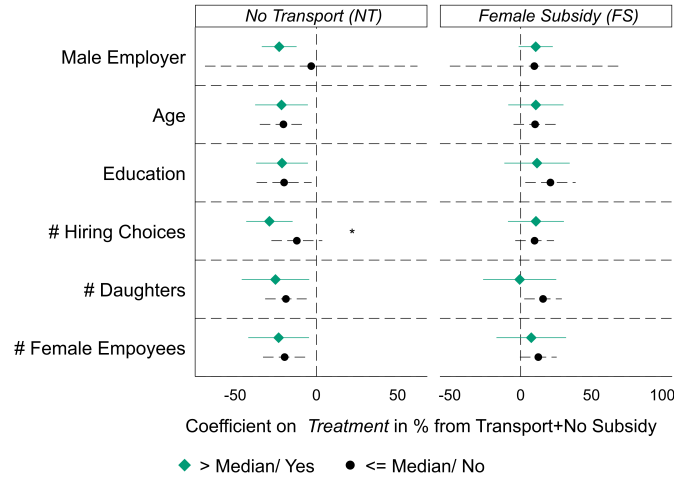
C.1 Figures

Figure C.8: Hiring by Transport Information, Female Subsidy and Other-Regarding Preferences



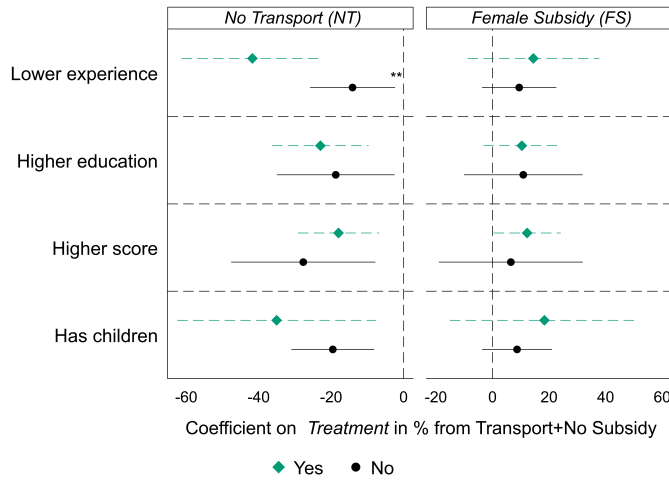
Notes: The graph shows the coefficients on the *No Transport* and *Female Subsidy* indicators from regression 3, respectively. Regressions are run separately among different subsets of employers (see section 4.2). That is, each coefficient shows how much employers in that group reduce female hiring when they do not know about the safe transport or increase female hiring when they know about the female subsidy. 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 C.9: Hiring by Transport and Female Subsidy Information and Employer Characteristics



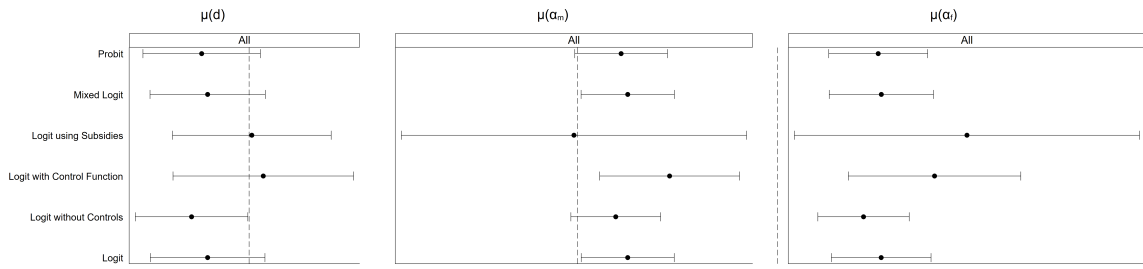
Notes: The graphs show the coefficients on the *No Transport* and the *Female Subsidy* indicators from regression 3 run separately within different employer subsamples. We do not include applicant fixed effects for insufficient observations and instead control for all characteristics of both applicants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

Figure C.10: Hiring by Transport and Female Subsidy Information and Applicant Characteristics



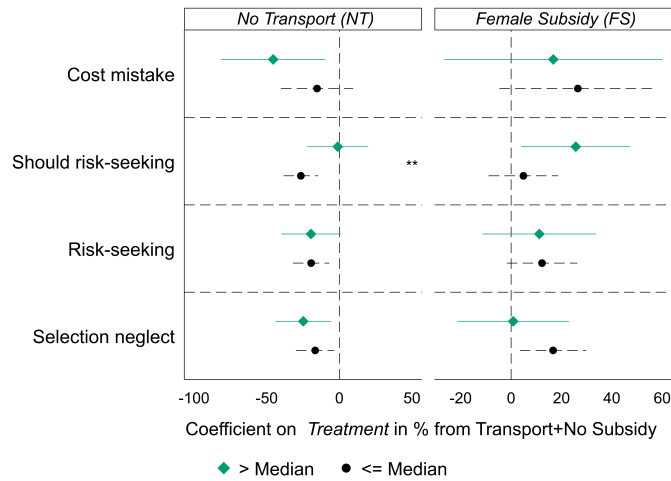
Notes: The graphs show the coefficients on the *No Transport* and the *Female Subsidy* indicators from regression 3 run separately within different pairs. We do not include applicant fixed effects for insufficient observations and instead control for all characteristics of both applicants shown to the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

Figure C.12: Parameter Robustness



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

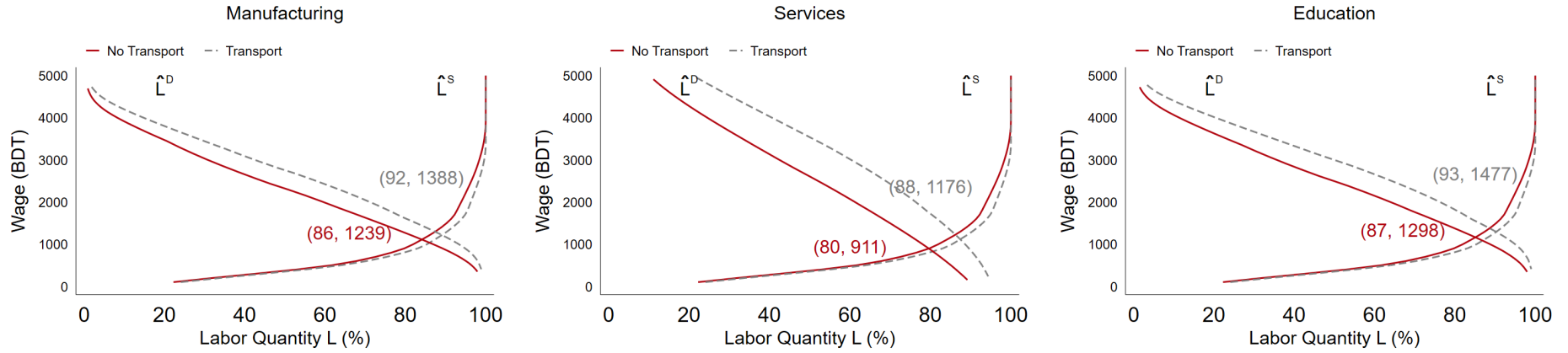
Figure C.11: Hiring by Transport and Female Subsidy Information and Employer Characteristics



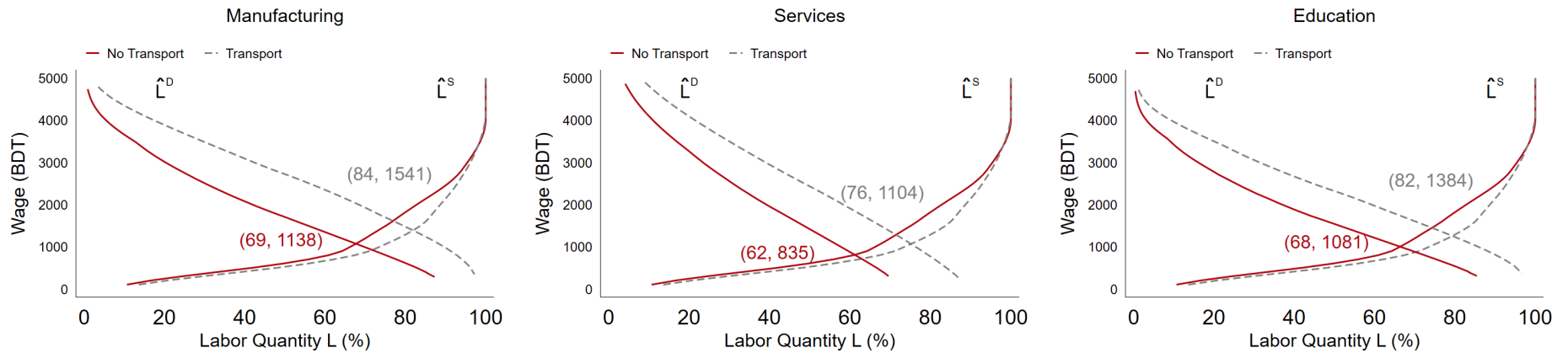
Notes: The graphs show the coefficients on the *No Transport* and the *Female Subsidy*. We run the regressions in different subsets of employers (see section 4.2). We do not include applicant fixed effects for insufficient observations and instead control for all characteristics of both applicants shown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

Figure C.13: Equilibria in the Male and Female Labor Markets using the Preferred Piece Rate

(C.13.1) Market for Male Workers



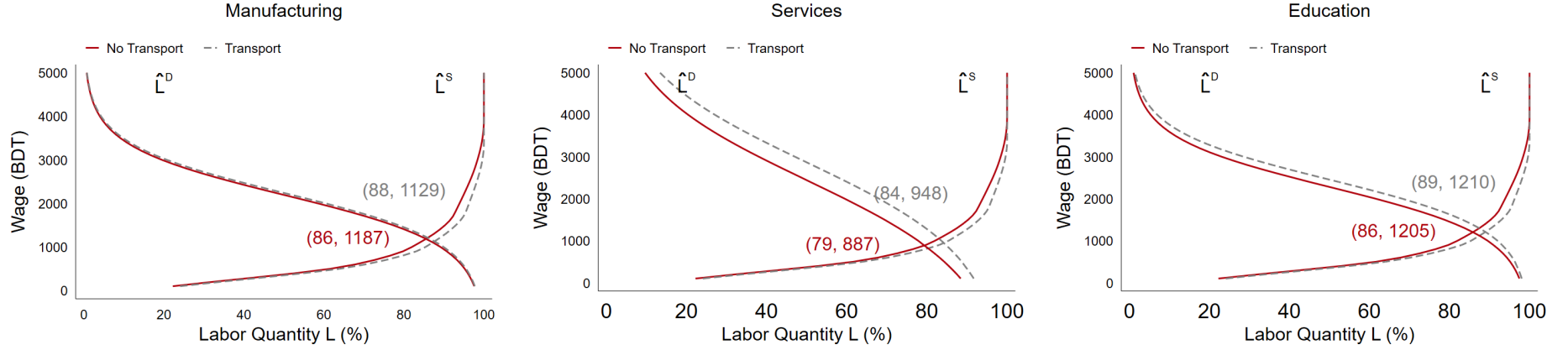
(C.13.2) Market for Female Workers



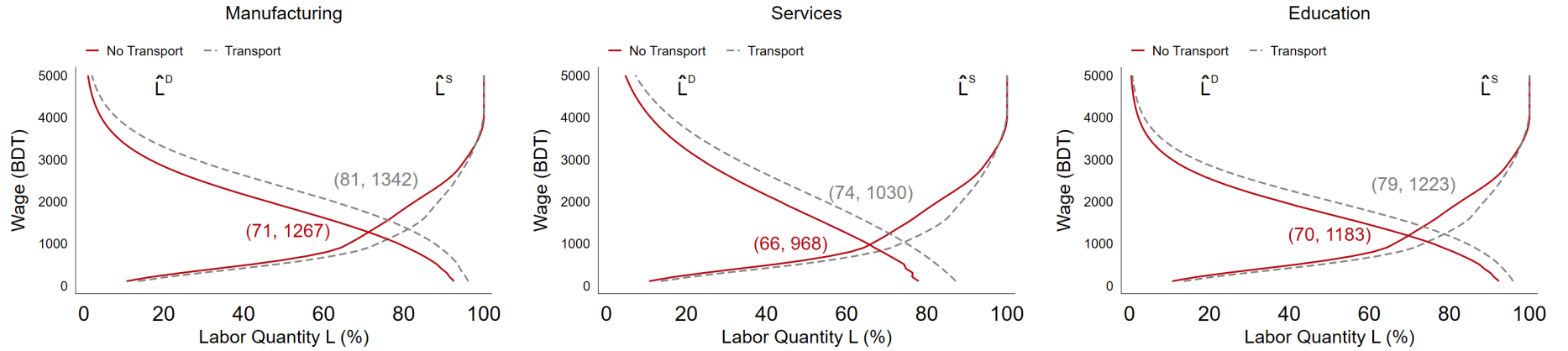
Notes: The graph shows the share of male and female workers demanded and the share of male and female workers supplied from equation 7 at each wage on a grid from 0 to 5,000 with and without transport by industry. We use predicted productivity and cost beliefs from the *Beliefs-Elicitation* employers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

Figure C.14: Equilibria in the Male and Female Labor Markets using the Experimental Payoffs

(C.14.1) Market for Male Workers



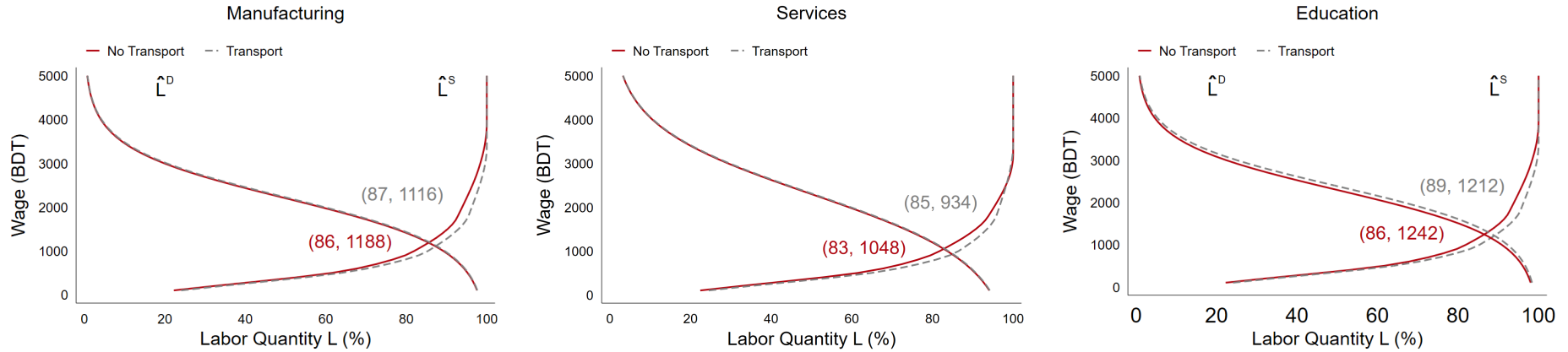
(C.14.2) Market for Female Workers



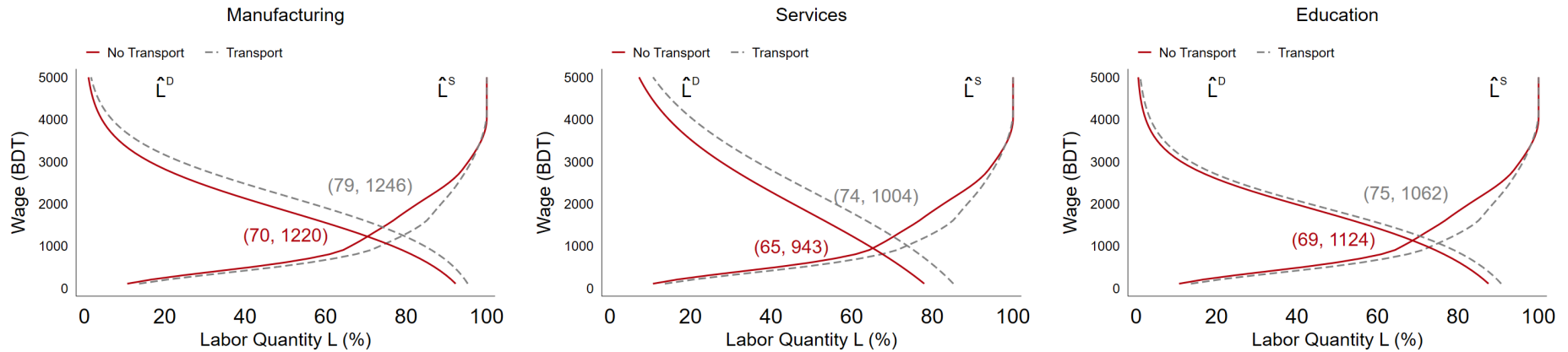
Notes: The graph shows the share of male and female workers demanded and the share of male and female workers supplied from equation 7 at each wage on a grid from 0 to 5,000 with and without transport by industry. We use predicted productivity and cost beliefs from the *Beliefs-Elicitation* employers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

Figure C.15: Equilibria in the Male and Female Labor Markets, Holding Selection and Productivity Constant Across Wages and Transport Conditions

(C.15.1) Market for Male Workers



(C.15.2) Market for Female Workers



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

C.2 Tables

Table C.1: Employer Characteristics, by Industry

	Manufacturing		Services		Education	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Female (%)	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 that is 1 if the applicant has children.

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

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

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

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

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

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

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

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

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

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

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

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

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

	Hired Woman (%)	# Women
	(1)	(2)
No transport (NT)	-0.016 (0.023)	-0.987*** (0.239)
Male subsidy (MS)	-0.033 (0.040)	-0.632** (0.270)
Female subsidy (FS)	0.003 (0.027)	0.573** (0.250)
Employer subsidy (ES)	0.024 (0.015)	2.005*** (0.298)
NT*MS	-0.001 (0.062)	0.105 (0.398)
NT*FS	0.012 (0.038)	-0.276 (0.388)
NT*ES	-0.014 (0.035)	0.393 (0.515)
Control Mean	0.979	4.598
Observations	460	446

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

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

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

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

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

	Male Workers								Female Workers							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(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
Control Mean	(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)
Observations	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
	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 5). We always control for assignment to the *High promotion* treatment and its interaction with *No transport*. We winsorize the data at the 95th percentile and control for the worker’s education, marriage status (unmarried, married without children, or married with children), work experience, Excel screening score, and age in the main specification in columns (1) and (9). We use a reservation wage of \leq BDT 1,500 (the wage in the hiring experiment) as an outcome in columns (2) and (10). We truncate the data at the 95th percentile in columns (3) and (11) and do not exclude outliers in columns (4) and (12). We exclude all covariates in columns (5) and (13) and include covariates selected using the post-double selection (PSD) Lasso method of Belloni et al. (2014) in columns (6) and (14). We 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).

Table C.9: Employer Preferences: Parameter Estimates, Mixed logit

	Pooled		Manufacturing		Services		Education	
	μ	σ	μ	σ	μ	σ	μ	σ
d	-0.109 (0.077)	0.000 (0.133)	-0.021 (0.118)	0.000 (0.226)	-0.055 (0.230)	0.000 (0.306)	-0.195* (0.108)	0.000 (0.190)
α_m	0.112** (0.053)	0.000 (0.133)	0.015 (0.075)	0.000 (0.226)	0.271 (0.183)	0.000 (0.306)	0.113 (0.073)	0.000 (0.190)
α_f	0.169*** (0.043)	0.018 (0.133)	0.173*** (0.059)	0.000 (0.226)	0.242* (0.126)	0.099 (0.307)	0.148** (0.067)	0.172 (0.186)
$p\text{-val } (\alpha_m = \alpha_f)$	0.236		0.033		0.834		0.592	
Observations	1,826		610		592		624	

Notes: Notes: The table presents parameter estimates from equation 5 estimated among all mixed-gender hiring pairs. We estimate heterogeneous preferences using the two hiring choices per employer. All estimates in money metric. d in '000 BDT. Standard errors are calculated using the delta method. We present p-values from testing whether α_m is statistically different from α_f .

Table C.10: Employer Preferences: Heterogeneity by Other-Regarding Index

	\leq Median	$>$ Median
d	-0.220** (0.111)	-0.054 (0.120)
α_m	0.024 (0.072)	0.182* (0.095)
α_f	0.060 (0.055)	0.264*** (0.077)
$p\text{-val } (\alpha_m = \alpha_f)$	0.543	0.285
Observations	916	910

Notes: The table shows coefficients and standard errors from equation 6. We divided the sample by the median other-regarding index used to test prediction 4. All estimates in money metric. d in '000 BDT.

Table C.11: Control Functions

	Outcome: Π_{ki}				Outcome: \mathcal{W}_{ki}			
	Pooled	Manufacturing	Services	Education	Pooled	Manufacturing	Services	Education
		$j = 1$	$j = 2$	$j = 3$		$j = 1$	$j = 2$	$j = 3$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.038*** (0.009)	-0.042*** (0.013)	-0.048*** (0.017)	-0.022 (0.019)	-1.372*** (0.105)	-1.411*** (0.197)	-1.328*** (0.171)	-1.374*** (0.182)
No transport (NT)	0.004 (0.010)	0.054*** (0.017)	-0.013 (0.017)	-0.018 (0.017)	-0.936*** (0.099)	-1.413*** (0.201)	-0.814*** (0.158)	-0.641*** (0.165)
Employer subsidy (ES)	-0.004 (0.011)	0.037** (0.018)	-0.028 (0.019)	-0.016 (0.018)	0.104 (0.081)	0.010 (0.159)	0.136 (0.096)	0.171 (0.156)
Male subsidy (MS)	0.007 (0.014)	0.010 (0.023)	-0.036** (0.018)	0.046* (0.026)	0.889*** (0.094)	0.721*** (0.179)	0.765*** (0.139)	1.146*** (0.168)
Female subsidy (FS)	-0.017 (0.011)	-0.002 (0.016)	-0.035 (0.024)	-0.011 (0.020)	0.183** (0.090)	0.156 (0.143)	0.084 (0.132)	0.235 (0.190)
NT*ES	-0.014 (0.017)	-0.083*** (0.026)	0.020 (0.036)	0.005 (0.032)	0.353** (0.176)	0.762** (0.325)	0.748*** (0.223)	-0.345 (0.315)
NT*MS	0.031 (0.019)	-0.005 (0.035)	0.096*** (0.032)	-0.001 (0.032)	0.472*** (0.174)	1.195*** (0.311)	0.299 (0.298)	0.113 (0.291)
NT*FS	0.026 (0.017)	-0.007 (0.027)	0.026 (0.035)	0.037 (0.028)	0.075 (0.164)	0.291 (0.286)	0.458* (0.240)	-0.304 (0.328)
NT*Female	0.001 (0.014)	-0.007 (0.024)	0.006 (0.024)	-0.003 (0.024)	-0.798*** (0.168)	-0.321 (0.326)	-0.945*** (0.277)	-1.031*** (0.283)
ES*Female	1.008*** (0.015)	0.986*** (0.024)	1.023*** (0.028)	1.007*** (0.027)	0.039 (0.163)	-0.276 (0.316)	0.506** (0.245)	-0.068 (0.272)
MS*Female	-0.015 (0.018)	-0.008 (0.028)	0.030 (0.029)	-0.069** (0.035)	-1.532*** (0.185)	-1.630*** (0.335)	-1.256*** (0.288)	-1.720*** (0.345)
FS*Female	-0.005 (0.016)	0.002 (0.023)	-0.003 (0.032)	-0.026 (0.029)	1.032*** (0.178)	0.592* (0.317)	1.549*** (0.274)	1.067*** (0.322)
NT*ES*Female	-0.009 (0.024)	0.016 (0.036)	-0.003 (0.052)	-0.016 (0.044)	0.232 (0.311)	0.183 (0.553)	-0.059 (0.494)	0.399 (0.530)
NT*MS*Female	-0.005 (0.027)	0.028 (0.049)	-0.052 (0.047)	0.025 (0.044)	0.331 (0.294)	0.349 (0.496)	0.361 (0.489)	0.321 (0.513)
NT*FS*Female	-0.004 (0.024)	-0.003 (0.038)	0.010 (0.048)	0.003 (0.040)	0.047 (0.278)	-0.107 (0.473)	-0.231 (0.467)	0.445 (0.526)
Male Mean (NT+NS)	0.693	0.664	0.713	0.700	1.009	0.980	1.113	0.913
F-Stat	739.905	388.760	187.621	305.291	88.860	54.230	33.753	36.917
Observations	1826	624	592	610	1826	624	592	610

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

Table C.12: Second-Stage Regression with fitted residuals, Outcome: Hired

	Pooled	Manufacturing	Services	Education
		$j = 1$	$j = 2$	$j = 3$
	(1)	(2)	(3)	(4)
Π (BDT '000)	1.491*** (0.210)	1.932*** (0.367)	1.106*** (0.351)	1.637*** (0.422)
Female	0.056 (0.179)	-0.122 (0.393)	-0.174 (0.328)	0.446 (0.303)
\mathcal{W}_m (BDT '000)	0.308*** (0.111)	0.389 (0.266)	0.221 (0.214)	0.284 (0.176)
\mathcal{W}_f (BDT '000)	0.382*** (0.090)	0.418 (0.259)	0.203 (0.143)	0.551*** (0.133)
$\widehat{\varepsilon}^\Pi$ (BDT '000)	0.962 (0.946)	0.570 (2.009)	0.195 (1.545)	2.083 (1.589)
$\widehat{\varepsilon}^\mathcal{W}$ (BDT '000)	-0.177 (0.109)	-0.183 (0.278)	0.094 (0.179)	-0.396** (0.178)
Observations	1826	624	592	610

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

Table C.13: Counterfactuals: Benchmarking the Importance of Paternalistic Discrimination

	Status Quo	$\alpha_m \mathcal{W}_m^E = \alpha_f \mathcal{W}_f^E$	$\mathcal{W}_m^E = \mathcal{W}_f^E$	$\alpha_m = \alpha_f$	$d = 0$	$\Pi_m^E = \Pi_f^E$	$L_m^S = L_f^S$	$\mathcal{W}_g^E = \mathcal{W}_g^{E:A}$	$\mathcal{W}_g^E = \mathcal{W}_g^A$
L_m^* (%)	85.00	85.00	85.00	85.00	85.00	85.00	85.00	85.00	86.00
L_f^* (%)	67.00	71.00	71.00	69.00	68.00	71.00	73.00	68.00	73.00
$L_m^* - L_f^*$ (ppts)	18.00	14.00	14.00	16.00	17.00	14.00	12.00	17.00	13.00
w_m^* (BDT)	1153.00	1153.00	1153.00	1153.00	1153.00	1153.00	1153.00	1178.00	1221.00
w_f^* (BDT)	1022.00	1285.00	1277.00	1118.00	1099.00	1239.00	706.00	1087.00	1398.00
$w_m^* - w_f^*$ (BDT)	131.00	-132.00	-124.00	35.00	54.00	-86.00	447.00	91.00	-177.00
\mathcal{W}_m^E ('000 BDT)	-128.97	-128.97	-128.97	-128.97	-128.97	-128.97	-128.97	-118.45	-101.54
\mathcal{W}_m^A ('000 BDT)	219.08	219.08	219.08	219.08	219.08	219.08	219.08	229.60	250.61
\mathcal{W}_f^E ('000 BDT)	-832.52	-789.33	-792.14	-824.58	-819.03	-805.96	-1037.58	-823.07	-770.73
\mathcal{W}_f^A ('000 BDT)	109.36	204.54	201.72	145.07	136.57	188.92	77.50	132.53	251.13

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 gender employment gap, L_m^* , L_f^* , $L_m^* - L_f^*$ (in percentage points), 2) male and female wages as well as the gender wage gap, w_m^* , w_f^* , $w_m^* - w_f^*$ (in BDT), 3) total male welfare as perceived by employers, \mathcal{W}_m^E (in '000 BDT), and applicants, \mathcal{W}_m^A (in '000 BDT), 4) total female welfare as perceived by employers, \mathcal{W}_f^E (in '000 BDT) and applicants, \mathcal{W}_f^A (in '000 BDT).

Table C.14: Counterfactuals: Benchmarking the Importance of Paternalistic Discrimination Across Industries

	Status Quo	$\alpha_m \mathcal{W}_m^E = \alpha_f \mathcal{W}_f^E$	$\mathcal{W}_m^E = \mathcal{W}_f^E$	$\alpha_m = \alpha_f$	$d = 0$	$\Pi_m^E = \Pi_f^E$	$L_m^S = L_f^S$	$\mathcal{W}_g^E = \mathcal{W}_g^{E:A}$	$\mathcal{W}_g^E = \mathcal{W}_g^A$
Manufacturing									
L_m^* (%)	86.00	86.00	86.00	86.00	86.00	86.00	86.00	87.00	86.00
L_f^* (%)	69.00	73.00	74.00	73.00	69.00	73.00	77.00	76.00	70.00
$L_m^* - L_f^*$ (ppts)	17.00	13.00	12.00	13.00	17.00	13.00	9.00	11.00	16.00
w_m^* (BDT)	1239.00	1239.00	1239.00	1239.00	1239.00	1239.00	1239.00	1246.00	1242.00
w_f^* (BDT)	1138.00	1403.00	1412.00	1386.00	1158.00	1358.00	808.00	1531.00	1179.00
$w_m^* - w_f^*$ (BDT)	101.00	-164.00	-173.00	-147.00	81.00	-119.00	431.00	-285.00	63.00
\mathcal{W}_m^E ('000 BDT)	-42.13	-42.13	-42.13	-42.13	-42.13	-42.13	-42.13	-39.60	-40.85
\mathcal{W}_m^A ('000 BDT)	258.27	258.27	258.27	258.27	258.27	258.27	258.27	264.29	259.55
\mathcal{W}_f^E ('000 BDT)	-742.60	-689.57	-695.72	-695.72	-735.77	-705.83	-960.39	-669.44	-739.15
\mathcal{W}_f^A ('000 BDT)	151.90	252.94	259.70	246.79	155.94	236.68	108.15	266.97	165.47
Services									
L_m^* (%)	80.00	80.00	80.00	80.00	80.00	80.00	80.00	83.00	81.00
L_f^* (%)	62.00	69.00	69.00	61.00	63.00	67.00	66.00	72.00	64.00
$L_m^* - L_f^*$ (ppts)	18.00	11.00	11.00	19.00	17.00	13.00	14.00	11.00	17.00
w_m^* (BDT)	911.00	911.00	911.00	911.00	911.00	911.00	911.00	1076.00	969.00
w_f^* (BDT)	835.00	1148.00	1155.00	792.00	861.00	1044.00	572.00	1308.00	903.00
$w_m^* - w_f^*$ (BDT)	76.00	-237.00	-244.00	119.00	50.00	-133.00	339.00	-232.00	66.00
\mathcal{W}_m^E ('000 BDT)	-222.24	-222.24	-222.24	-222.24	-222.24	-222.24	-222.24	-156.82	-195.94
\mathcal{W}_m^A ('000 BDT)	178.71	178.71	178.71	178.71	178.71	178.71	178.71	186.95	139.54
\mathcal{W}_f^E ('000 BDT)	-845.17	-817.90	-815.51	-844.52	-850.70	-828.68	-990.33	-795.88	-850.89
\mathcal{W}_f^A ('000 BDT)	95.36	155.32	154.91	80.84	102.53	116.65	33.70	215.61	117.46
Education									
L_m^* (%)	87.00	87.00	87.00	87.00	87.00	87.00	87.00	89.00	88.00
L_f^* (%)	68.00	72.00	72.00	68.00	70.00	72.00	75.00	74.00	69.00
$L_m^* - L_f^*$ (ppts)	19.00	15.00	15.00	19.00	17.00	15.00	12.00	15.00	19.00
w_m^* (BDT)	1298.00	1298.00	1298.00	1298.00	1298.00	1298.00	1298.00	1391.00	1331.00
w_f^* (BDT)	1081.00	1324.00	1321.00	1112.00	1225.00	1320.00	767.00	1443.00	1161.00
$w_m^* - w_f^*$ (BDT)	217.00	-26.00	-23.00	186.00	73.00	-22.00	531.00	-52.00	170.00
\mathcal{W}_m^E ('000 BDT)	-120.57	-120.57	-120.57	-120.57	-120.57	-120.57	-120.57	-82.37	-107.58
\mathcal{W}_m^A ('000 BDT)	285.00	285.00	285.00	285.00	285.00	285.00	285.00	332.53	302.66
\mathcal{W}_f^E ('000 BDT)	-893.49	-858.91	-859.98	-883.06	-869.88	-860.34	-1118.15	-839.18	-879.31
\mathcal{W}_f^A ('000 BDT)	130.51	221.32	220.25	140.95	181.41	219.89	90.11	271.05	156.96

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

Table C.15: Counterfactuals: Estimating the Welfare Effects of Transport and Subsidy Interventions

	Status Quo	Govt Trans	Subsidies	Empl Trans
L_m^* (%)	85.00	85.00	85.00	85.00
L_f^* (%)	67.00	81.00	78.00	31.00
$L_m^* - L_f^*$ (ppts)	18.00	4.00	7.00	54.00
w_m^* (BDT)	1153.00	1153.00	1153.00	1153.00
w_f^* (BDT)	1022.00	1314.00	1685.00	379.00
$w_m^* - w_f^*$ (BDT)	131.00	-161.00	-532.00	774.00
\mathcal{W}_m^E ('000 BDT)	-128.97	-128.97	-128.97	-128.97
\mathcal{W}_m^A ('000 BDT)	219.77	219.77	219.77	219.77
\mathcal{W}_f^E ('000 BDT)	-832.52	-190.41	-710.68	-511.03
\mathcal{W}_f^A ('000 BDT)	108.94	229.82	450.85	31.78
Π ('000 BDT)	791.75	906.53	929.17	681.87
Total Cost ('000 BDT)	0.00	320.76	347.49	0.00

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