

# Scaling Up to Decrease the Divide: Firm Size and Female Employment\*

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## Abstract

We examine whether female employment share systematically varies with the size of a firm. Using firm and individual-level data, we first document that the share of female employees increases with firm size. We next exploit labor law reforms in India that raised firm-size thresholds for regulatory compliance and strengthened the overall business environment using a difference-in-differences design. We find that treated states experienced a 4 percent rise in employment, a 13 percent increase in output, along with a 5 percent increase in the female worker share. We further show that larger firms provide amenities such as maternity benefits, transport, and paid leave, which women value relatively more, plausibly contributing to these effects. Overall, our results suggest that policies that facilitate firm growth can also increase female employment.

**JEL Codes:** J20, J16, L25, L50

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# 1 Introduction

Low female labor force participation (FLFP) continues to represent a major source of lost productivity across countries. While in OECD countries, the female labor force participation rate stands at 78% of that of men, in South Asia, the gap widens significantly, with the ratio of female to male labor force participation equaling 44% <sup>1</sup>. Existing literature largely discusses the role played by income, education, and social norms as potential explanations behind this disparity; however, the differential demand for women due to variation in firm attributes, which can also constrain the availability of suitable labor market opportunities for them, has received far less attention. In particular, little is known about the constraints that the size of a firm may exhibit towards employing women; thereby, the firm size distribution in a country can have aggregate implications for the gender composition in labor markets.

Cross-country evidence shows a significantly positive association between FLFP and average firm size (Appendix Figure A.1, Panel (a)), even after accounting for the income effect (Panel (b)).<sup>2</sup> If job attributes systematically differ such that jobs in bigger firms are more attractive for women relative to men, then the firm-size distribution may be a limiting factor for female employment in a country. Theoretically, bigger firms, which are more productive, can find it profitable to provide non-wage amenities valued relatively more by women, like creches, maternity benefits, transport, etc., and attract more women into the workforce. This paper investigates the relationship between firm size and female employment and whether policies that spur firm growth can also increase female employment. We examine this question in the context of India, characterized by low FLFP rates of around 27 percent (ILO estimates) and a country dominated by small firms – almost 75 percent of the non-farm workforce in India is employed in firms having less than 10 employees (Figure A.2).<sup>3</sup>

Using firm-level data from the Annual Survey of Industries (ASI) from 1998-2019, a

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<sup>1</sup>Source: International Labor Organization, 2024.

<sup>2</sup>The figures plot data for 156 countries using data from the OECD report and World Bank Enterprise Data for firm size in the formal sector, and Our World in Data for FLFP rates. The elasticity estimate between FLFP and firm size using the cross-country data is 0.16.

<sup>3</sup>This proportion stands at 20 percent for the United States (Current Population Survey 2000-2021).

nationally representative panel data on registered (or formal) manufacturing establishments in India we first document a positive relationship (an elasticity of 0.2) between share of female workers and firm size (Figure 1), controlling for unobserved heterogeneity at the establishment, industry and state level over time. This positive relationship is statistically significant and robust to using alternative definitions of female employment, firm size, and controlling for firm exports. We supplement this analysis by using cross-sectional data from the Economic Census of India (1998, 2005, 2013) and nationally representative household surveys (1999-2019), which shows the persistence of this relationship across other economic sectors including agriculture, construction and services and controls for individual characteristics and variation across district-year and industry-occupation-year levels. We also show that this relationship is not unique to India. Using individual-level data from the Current Population Survey (2000-2021), we document that female employees are more likely to work in larger firms, even in the United States (U.S.).

To alleviate concerns of potential endogeneity, we use exogenous variation in labor law amendments across states of India related to firm size-based restrictions and study their impact on share of female employment in a firm. These amendments increased the employment thresholds associated with certain regulations<sup>4</sup>, thereby reducing the cost of employment expansion for firms, incentivizing them to grow. These amendments were enacted by five states in the country—Rajasthan (2014), Jharkhand (2017), Maharashtra (2016), Madhya Pradesh (2015) and Uttar Pradesh (2018)—which combined house more than 500 million people, exceeding the population of countries like the United States. These regulations have previously been shown to constrain firm size in India (Amirapu & Gechter, 2020).

We estimate the causal impact of the amendments on female workforce share, firm size, and related firm outcomes using a differences-in-differences framework. In a two-way fixed effects specification, the amendments raise the proportion of female workers by 4 percent in treated states, accompanied by increases in the number of female workers, female mandays,

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<sup>4</sup>These regulatory changes are described in detail in Section 4.

and the likelihood that an establishment hires a woman. Applying recent methods for staggered adoption ([Callaway & Sant’Anna, 2021](#)) yields a 5 percent rise in female share. We also observe a 4 percent increase in employees and a 13 percent increase in output post-amendments, indicating that growth-enabling policies can boost female employment. An event study design confirms no differential pre-treatment trends across treated and control states. Nevertheless, to check the robustness of our results, we use the Synthetic Difference-in-Differences (SDID) estimator by [Arkhangelsky, Athey, Hirshberg, Imbens, and Wager \(2021\)](#), which constructs a weighted control to enforce parallel trends.

We test alternative channels beyond firm size growth, which can also explain the increase in the share of female workers after the reforms—entry-driven labor demand, export adoption, reduced union power, and turnover-driven compositional change—and find little empirical support for any of them.

Next, we examine what explains the positive relationship between firm size and female employment share. Using a theoretical framework, we show that three mechanisms can potentially explain this: (i) bigger firms provide better non-wage amenities that women value relatively more, (ii) task requirements vary with firm size in ways that raise demand for women’s work in bigger firms, and (iii) bigger firms discriminate less against women.

First, we show that differential task requirements cannot be the only driver: in the individual-level analyses, the positive association between relative female employment and firm size persists even after controlling for detailed occupation content. Moreover, the ASI reports gender-disaggregated employment only for production workers, for whom task variation with firm size is likely to be limited. Together, these results point to mechanisms beyond task composition.

Second, the individual-level data reveal two key patterns. Women are 11–14 percent more likely than men to be employed in jobs that offer maternity/health benefits and written contracts (a proxy for job stability), and nearly 80 percent are more likely to work part-time. This is consistent with women placing greater weight on non-wage amenities, documented

more generally in other contexts too by existing studies (Mas & Pallais, 2017; Wiswall & Zafar, 2018). We also find that workers in larger firms (20+ employees) are substantially more likely to receive these amenities: 70 percent more likely to receive maternity benefits, 45 percent more likely to receive paid leave, and 50 percent more likely to have a written contract vs. firms with fewer than six workers. We corroborate these patterns using crowd-sourced employee reports from an online platform. Consistent with this mechanism, the labor-law amendments are also associated with higher welfare expenditure per employee. In line with the model, higher productivity and profits in larger firms, and lower compliance costs after the amendments, can raise output and profitability, enabling greater spending on worker welfare.

Finally, we examine whether larger firms discriminate less against women. To do this, we undertake an audit-study experiment by sending identical female and male candidate profiles across four industries in the service sector. While we find that female profiles are 25 percent less likely to receive a callback, bigger firms are either more likely or equally likely than smaller firms to give lower callbacks to similar female profiles. While this result is not representative of the economy, it provides suggestive evidence that discrimination cannot solely explain this positive relationship between firm size and female employment.<sup>5</sup>

Taken together, these findings are most consistent with an amenities-based mechanism: larger firms employ more women, in part, because they provide non-wage amenities that women value relatively more. A natural next question is why larger firms provide these amenities. Some are legally mandated, for example, creches above specified employment thresholds of 50 and maternity benefits above the minimum establishment size of 10. If compliance with these requirements were the sole reason, we should find a discontinuous relationship between firm-size and share of female workers with a sharp spike beyond the prescribed thresholds. However, we do not find such spikes in the data. Second, firms could

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<sup>5</sup>It could also be that bigger firms have diversity targets and specifically look to hire women. However, this would lead to lower profits for bigger firms, and we do not find a fall in the profit per employee as firm size increases.

offset these costs through lower wages for women. We do not find evidence of a larger gender wage gap in bigger firms; if anything, the gap is smaller in larger firms in the individual-level data. Our model rationalizes this pattern if amenities raise women’s productivity and improve matching, allowing larger firms to profitably incur fixed costs of family-friendly policies while attracting and retaining more productive women.<sup>6</sup>

Our work contributes to several strands of the literature. First, we contribute directly to the literature on firm-level determinants of female employment. Surprisingly, there has been little research in this area, with most attention paid to a firm’s export status (Banerjee, Chakraborty, & Castro Peñarrieta, 2022; Juhn, Ujhelyi, & Villegas-Sanchez, 2014; Ozler, 2000). In a recent study, Chiplunkar and Goldberg (2024) show that female worker shares are higher in women-owned enterprises, and hence, removing barriers to female entrepreneurship can be an effective policy solution to increase female employment and aggregate economic productivity. However, other attributes, such as firm size, have not gained much attention in the literature. Our study offers the first comprehensive evaluation of the association between firm size and female employment.<sup>7</sup> We not only use nationally representative data, accounting for unobservables at the firm, industry, occupation, and location levels, but also causally estimate the impact of policy instruments that induce firm growth on the share of female workers. Further, we examine the mechanisms that explain this relationship.

Second, we contribute to the literature that examines the relationship between firm size and non-wage job amenities. Existing literature shows that employer-provided welfare like child-care assistance (financial assistance for child-care, on-site child care), maternity, parental, and sick-child leave, and extended maternity leave are more likely in larger firms (Hayghe, 1988; Machado, Neto, & Szerman, 2024). However, larger firms can also have inflexible schedules and longer working hours (Shao, Sohail, & Yurdagul, 2021). We extend

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<sup>6</sup>Very large firms may also be more likely to maintain dedicated HR functions that design and implement family-friendly workplace policies (Glass & Estes, 1997).

<sup>7</sup>Mitra (2003) document this relationship descriptively, not controlling for unobservables for a sample of 2240 US professional workers, and Carter, Simkins, and Simpson (2003) documents this only in the context of female presence on boards

this literature by showing how the female share among employees changes with the changes in benefits across firm sizes. Our results are consistent with the literature that documents equal or greater preference for non-pecuniary benefits among women (Erosa, Fuster, Kambourov, & Rogerson, 2022; Goldin, 2014; Mas & Pallais, 2017; Wiswall & Zafar, 2018), which in turn has implications for the resulting gender wage gap across firms (Morchio & Moser, 2024).

Lastly, while the existing literature studies the effects of labor regulations on employment (Besley & Burgess, 2004; Botero, Djankov, Porta, Lopez-de Silanes, & Shleifer, 2004; Kahn, 2007; Lee & Park, 2023) and productivity (Autor, Kerr, & Kugler, 2007; Dougherty, Robles, & Krishna, 2011), none of the studies examine the effects of these regulations on the gender composition of workers. Our paper fills this gap and shows that one of the mechanisms through which relaxing labor regulations increases female employment is by increasing firm size.<sup>8</sup> In general, the literature studying the effect of policies on female employment mostly focuses on laws offering protection or benefits to women (maternity and parental leave, equal pay and anti-discriminatory laws, wage transparency laws), which in some cases have unintended consequences of reducing employer demand for them.<sup>9</sup> We extend this literature by showing that policies that are not explicitly targeted towards women can also spur employment for them.

The next section proposes a model that motivates our question and provides testable mechanisms. Section 3 presents descriptive evidence on the relationship between firm size and relative female employment and Section 4 evaluates the effect of the labor law amendments. Section 5 discusses the mechanisms, and Section 6 concludes.

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<sup>8</sup>Studies also examine the impact of state-level variation in labor regulations on firm adjustment to various shocks like trade reforms (Hasan, Mitra, & Ramaswamy, 2007), rainfall variation (Adhvaryu, Chari, & Sharma, 2013; Chaurey, 2015), dismantling the License Raj (Aghion, Burgess, Redding, & Zilibotti, 2008), among others. See Chaurey (2015) for a review.

<sup>9</sup>In the Indian context, Bose and Chatterjee (2024) find a reduction in female employment due to Maternity Benefits Act passed in 2017 (MBAA). Bhalotra, Chatterjee, Mahajan, Walia, and Wang (2024) find a reduction in the relative share of women in the mid-sized regulated firms after the Prevention of Sexual Harassment at Workplaces Act was passed in 2013.

## 2 Model

In this section, we develop a simple model of the labor market to discuss factors that can shape the relationship between firm size and female employment. We consider an economy with heterogeneous workers and a frictional labor market. The frictions that workers face in the labor market allow firms to enjoy market power.<sup>10</sup> A firm's productivity  $z$  follows a distribution  $F([\underline{z}, \bar{z}])$ , and it produces output, the price of which is normalized to 1, using only labor as its sole input. A firm hires both male ( $N_m$ ) and female ( $N_f$ ) workers who are assumed to be imperfect substitutes.<sup>11</sup>

Each worker receives a gender-specific wage and amenities,  $a \in \{1, \bar{a}\}$ . We assume that women value amenities, such that better amenities improve their average productivity,  $z_f$ , where  $z_f(\bar{a}) > z_f(1)$ . This can be interpreted in two ways: that the firm is able to attract higher-productivity women, or alternatively, the female workers are able to increase their productivity when better amenities are available.<sup>12</sup> For simplicity, we assume that amenities are standardized at  $a = 1$  for male workers, and their average productivity is normalized to 1. We assume that the cost of providing a basic set of amenities, i.e.,  $a = 1$ , is fixed and equals  $\bar{C}$ . Once firms decide to produce any positive output, this fixed cost does not affect their marginal decisions; hence, it can be normalized to equal 0. The cost of providing a better set of amenities,  $\bar{a}$ , is assumed to equal  $C > \bar{C}$ .<sup>13</sup>

A  $z$ -productivity firm produces output by hiring  $N_m$  male and  $N_f$  female workers and

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<sup>10</sup>As shown in Appendix B, the results of the model hold with competitive markets as well.

<sup>11</sup>This assumption is consistent with existing evidence (Ngai & Petrongolo, 2017; Olivetti & Petrongolo, 2014)

<sup>12</sup>This assumption is consistent with studies such as Bütikofer, Riise, and M. Skira (2021), which concludes that access to paid family leave improves maternal health, Chowdhury (2018) which finds positive effects of on-site childcare on female productivity, and Vara-Horna, Díaz-Rosillo, Asencios-Gonzalez, and Quipuzco-Chicata (2023) arguing that policies aimed to prevent workplace sexual harassment would improve worker productivity and particularly benefit women.

<sup>13</sup>In Appendix B we show an extension of the model environment with competitive markets, where amenities can take a continuum of values, and the cost of providing them varies with the size of the amenities. We further assume that men also value amenities and show that all the key predictions of the benchmark hold as long as women value amenities more than men.

providing amenities  $a$  using a CES production function, which is described below:

$$Y(N_m, N_f, a) = z \left\{ N_m^{\frac{\sigma-1}{\sigma}} + \tau(z) \{z_f(a) N_f\}^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\sigma}{\sigma-1}} \quad (1)$$

Here,  $\tau$  is the weight attached to female labor in production. Thus,  $\tau$  measures the importance of tasks where women have a comparative advantage, which is allowed to change with the productivity of firms;  $\tau < 1$  may also represent the degree of discrimination against women in a particular firm. The firm faces the following labor supply curves for men and women:

$$N_g = k_g a^\rho w^\epsilon \quad \rho, \epsilon, k_g > 0, g \in \{m, f\} \quad (2)$$

We assume that labor supplied by men and women increases with their wages and the level of amenities. Here,  $\epsilon$  and  $\rho$  capture the elasticity of labor supply with respect to wages and amenities, respectively. To capture the frictions that women face on the supply side, such as additional household responsibilities, care duties, or social norms, we assume  $k_f < k_m$ . Since  $a = 1$  for men,  $N_m = k_m w_m^\epsilon$ . Using the labor supply functions, we can rewrite wages in terms of employment:

$$w_m = \left( \frac{N_m}{k_m} \right)^{\frac{1}{\epsilon}}; \quad w_f = \left( \frac{N_f}{k_f a^\rho} \right)^{\frac{1}{\epsilon}} \quad (3)$$

As employment increases, wages offered by these firms need to go up to attract new workers. Further, wages and amenities are inversely related. This represents compensating differentials, i.e., firms can choose to provide lower wages and higher amenities to female workers, keeping their employment unchanged. Given this, the firm makes decisions regarding the number of male and female workers to hire and the level of amenities that they would provide.

We divide the problem into two steps. First, for a given level of amenities, we solve for the firm's decision regarding the number of workers they would hire. Given these decisions, firms choose the level of amenity that allows them to maximize profit.

Let us consider the profit maximization problem of a  $z$  – *type* firm providing amenities  $a \in \{1, \bar{a}\}$ .

$$\pi(z, a) = \max_{N_m, N_f} Y(N_m, N_f, a) - w_m(N_m)N_m - w_f(N_f, a)N_f \quad (4)$$

First order conditions yield the following relationships:

$$\frac{\partial Y}{\partial N_m} = w_m(N_m) + \frac{\partial w_m}{\partial N_m} N_m \quad (5)$$

$$\frac{\partial Y}{\partial N_f} = w_f(N_f, a) + \frac{\partial w_f}{\partial N_f} N_f \quad (6)$$

The LHS of equations 5 and 6 represents the marginal revenue product, and the RHS represents the marginal cost of hiring an additional male and female labor, respectively. The marginal revenue product decreases with employment due to diminishing marginal productivity. The marginal cost curve has two components: the wage that must be paid to the new worker hired and the increase in wages that must be paid to all existing workers; thus, it increases in employment. The equilibrium is reached at the level of employment where the marginal revenue product equals the marginal cost. As a firm's productivity goes up for a given level of amenities, the marginal revenue product increases at all levels of employment, thereby increasing the equilibrium number of male and female workers hired. Thus, higher productivity of firms is also associated with a larger workforce (Lucas Jr, 1978), as we also show empirically in Section 5. For a given level of amenities, each worker would also receive higher wages, attracting more workers to the market.

Using the first-order conditions and substituting for the functional forms, we obtain the following equilibrium female-to-male labor ratio:

$$\frac{N_f}{N_m} = \left\{ \tau(z) \{z_f(a)\}^{\frac{\sigma-1}{\sigma}} a^{\frac{\rho}{\epsilon}} \left\{ \frac{k_f}{k_m} \right\}^{\frac{1}{\epsilon}} \right\}^{\frac{1}{\frac{1}{\sigma} + \frac{1}{\epsilon}}} \quad (7)$$

This shows that the equilibrium ratio of female to male employees in a firm is higher for

firms where women have a comparative advantage or face a lower degree of discrimination (higher  $\tau$ ) and when the frictions associated with female labor supply relative to males are lower (higher  $\frac{k_f}{k_m}$ ). Since male and female workers are substitutes, such that the elasticity of substitution,  $\sigma > 1$ , higher amenities improve the average productivity of women and attract female workers willing to accept lower wages, thus incentivizing firms to hire more women relative to men. If  $\tau$  increases with firm size, and the larger firms are more likely to provide better amenities (we show it to be true later), the ratio of female to male workers rises with firm size. Under circumstances where  $\tau$  reduces with firm size, relative female employment increases only when the effect of the higher productivity of women exceeds the lower importance of female tasks or a higher degree of discrimination against them.

The equilibrium wage ratio is given by:

$$\frac{w_f}{w_m} = \left\{ \frac{k_m}{k_f a^\rho} \frac{N_f}{N_m} \right\}^{\frac{1}{\epsilon}} = \left\{ \frac{k_m}{k_f a^\rho} \right\}^{\frac{1}{\sigma+\epsilon}} \left\{ \tau(z) \{z_f(a)\}^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{1}{\frac{1}{\sigma}+\frac{1}{\epsilon}}} \quad (8)$$

Thus, the gender wage ratio (defined as the ratio of female to male wages) is higher for higher values of  $\tau$ . When women face greater frictions associated with their labor supply ( $\frac{k_f}{k_m}$  is lower), their reservation wage is higher. Thus, the gender wage gap is lower in both these cases. The effect of amenities on the wage ratio is ambiguous. This is because, while the productivity of female workers rises with amenities, thus incentivizing firms to substitute for more women, firms can choose to compensate women less by providing more amenities. Thus, the wage ratio could increase or decrease depending on whether the demand effect or the compensating differential effect dominates.

The firm's decision to provide higher amenities for women depends on which choice yields the maximum profit, as described below:

$$\Pi(z) = \max_{a \in \{\underline{a}, \bar{a}\}} \{ \pi(z, \bar{a}) - C, \pi(z, 1) \} \quad (9)$$

where  $C$  is the relative cost of providing the higher-valued amenities. Using the envelope

theorem:

$$\begin{aligned} \frac{\partial \pi^*(z, a)}{\partial z} &= \left\{ N_m^{\frac{\sigma-1}{\sigma}} + \tau(z) \{z_f(a) N_f\}^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\sigma}{\sigma-1}} \\ &\quad + z \frac{\sigma}{\sigma-1} \left\{ N_m^{\frac{\sigma-1}{\sigma}} + \tau(z) \{z_f(a) N_f\}^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{1}{\sigma-1}} \tau'(z) \{z_f(a) N_f\}^{\frac{\sigma-1}{\sigma}} \end{aligned} \quad (10)$$

Here, if  $\tau$  is non-decreasing or weakly decreasing with firm size,  $\frac{\partial \pi^*(a)}{\partial z} > 0$ . Further, as  $z_f(a) > z_f(1)$ ,  $\frac{\partial \pi^*(z, \bar{a})}{\partial z} > \frac{\partial \pi^*(z, 1)}{\partial z}$ . Thus, the difference in profits when firms provide higher versus lower amenities increases with their productivity and, therefore, with firm size. If  $\pi(\underline{z}, \bar{a}) - \pi(\underline{z}, 1) < C < \pi(\bar{z}, \bar{a}) - \pi(\bar{z}, 1)$ <sup>14</sup>, there exists a  $z^T$ , such that for all  $z > z^T$ , that is, the larger firms find it profitable to provide higher amenities.

To summarize, firms with higher productivity tend to be larger since they hire more men and women. These firms also find it profitable to provide better amenities to women, as a result of which female productivity is higher. The gender employment ratio increases for larger firms, and the effect on the wage ratio is ambiguous. If discrimination against women is lower in larger firms, this effect is amplified, whereas if it is substantially higher, the relationship is reversed.

### 3 Descriptive Evidence

We use multiple datasets to study the relationship between firm size and the proportion of female employees.

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<sup>14</sup>If the cost of providing better amenities is too small such that even the smallest firms can afford to pay for it,  $C < \pi(\underline{z}, \bar{a}) - \pi(\underline{z}, 1)$ , or alternatively, too large that none of the firms can afford to pay for it,  $C > \pi(\bar{z}, \bar{a}) - \pi(\bar{z}, 1)$ , then the relationship between firm size and the equilibrium gender employment gap and gender wage ratio solely depends on how the level of discrimination changes with firm size. In this case, there is no heterogeneity between firms in terms of the level of amenities that they provide, which, as we show later empirically, is not the case.

### 3.1 Firm level: Annual Survey of Industries

At the establishment level, our main data is the Annual Survey of Industries (ASI). It is a nationally representative panel survey of the registered manufacturing sector conducted annually by the National Sample Survey Organisation (NSSO).<sup>15</sup> For the purpose of this paper, we use the terms *firm* and *establishment* interchangeably since multi-establishment firms constitute a very small proportion of all manufacturing enterprises in India.<sup>16</sup> The establishment-level ASI data is available from 1998-2019 and establishment identifiers are provided for the period between 1998 and 2019.<sup>17</sup>

The ASI collects information on the number and type of employees in an establishment, such as the number of manufacturing workers, supervisors, other employees, and contract workers. For each type of employee, their days of work and total wage expenditure incurred by the firm are also recorded.<sup>18</sup> Gender-disaggregated employment data is captured only for manufacturing workers, including gender-disaggregated mandays and wages for the manufacturing workers. Since manufacturing workers constitute 72 percent of all permanent employees (workers, supervisors, and other employees), gender-disaggregated employment data is captured for a large proportion of permanent employees in a firm. The survey also provides data on other establishment characteristics: value of output, input expenditures including expenditures on employee welfare and contributions towards pension, raw materials,

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<sup>15</sup>The ASI data has two components: a census component whereby establishments employing over 100 workers or those located in the 6 least industrially developed states are captured every year, and a survey component, with a stratified random sample for establishments hiring less than 100 workers every year. Such establishments are typically surveyed once every 3 years. In the sample component, firms in each state are arranged into different groups based on their 4-digit industry classification, and 1/5<sup>th</sup> units are drawn from each state and 4-digit industry combination based on stratified circular systematic sampling.

<sup>16</sup>For instance, [Chakrabarti and Tomar \(2022\)](#) show that multi-plant establishments constitute only 5 percent of the manufacturing plants having at least USD 30 million sales in India. This number is then likely to be even smaller in the overall manufacturing sector since multi-plant firms are generally big in size.

<sup>17</sup>While panel identifiers from 1998-2009 are available in the public domain, we obtained these from the Ministry of Statistics and Program Implementation for 2010-2019. The district identifiers are available only between 1998 and 2009.

<sup>18</sup>Workers are employees engaged in manufacturing tasks. Supervisors are employees not directly involved in manufacturing tasks but are responsible for overall management and supervision. Permanent employees comprise workers, supervisors, and other employees. Contract workers are manufacturing workers hired on contractual terms by the establishment and are ineligible for the benefits and job security available to permanent employees.

etc., and capital expenditure. This allows us to define firm size using both employment and output measures.

Table A.1 shows the summary statistics of the main labor market variables. The proportion of female manufacturing workers is defined as the number of female workers out of the total manufacturing workers. The proportion of female mandays is similarly defined based on worker mandays. On average, women constitute 12 percent of total workers. Firm size based on employment is defined in terms of all paid employees (workers, supervisors, contract workers, and other employees). On average, a firm has 76 paid employees.<sup>19</sup> Alternatively, we also define firm size using the value of output (price  $\times$  quantity) produced by a firm. This is deflated by a two-digit industry-specific Wholesale Price Index (WPI) with 2004 as the base year. The gender wage gap in a firm is defined as the ratio of the female daily wage rate to the male daily wage rate. The female (male) daily wage rate is computed by dividing wages paid to female (male) workers by female (male) worker mandays. On average, women receive 86 percent of the wage rate as men.

Figure 1 shows the scatter plot (binned) of the proportion of female workers across firm size. We see an increase in the proportion of female workers as firm size increases upto almost 120-130, and then it stays almost constant thereafter.<sup>20</sup> We next examine if this relationship holds after controlling for other unobservable characteristics across firms.

### 3.1.1 Findings: Firm Level

We examine how the proportion of female workers (or mandays) varies with log of firm size exploiting both within-firm and across firm variation (details in Appendix C). Table 1, Panel

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<sup>19</sup>Appendix Figure A.3 shows the firm size distribution for firms across various time spans in our data using the measure of total employees. We keep firms with total employees up to 500, since 95 percent of the firms are below this threshold. This is done for ease of visual presentation. Clearly, even the registered firms in India are concentrated in the lower part of the distribution (less than 50 employees), with around 30 percent having less than 10 employees.

<sup>20</sup>Since many confounding factors can explain this association, we also check whether the type of enterprise matters (Figure A.4) or if there are regional differences (Figure A.5). We find that the relationship is steeper for private enterprises and is observed in both the northern and southern parts of India. We also find that the relationship is similar across time span (graphs omitted for brevity).

A, reports estimates with firm fixed effects. We find that a one percent increase in firm size (total employment) is associated with a 0.024 and 0.023 percentage-point increase in the share of female workers and female mandays, respectively (columns 1–2), implying roughly a 0.2 percent increase in the female share for a one percent increase in size. The magnitude remains similar when we control for industry and state-specific effects over time in columns (3) and (4). The magnitudes are similar when additionally controlling for industry-by-year and state-by-year effects (columns 3–4). Panel B, which omits firm fixed effects, yields qualitatively similar estimates, though slightly larger when industry and location effects are not included. Allowing for a quadratic in log firm size (columns 5–6) shows a predominantly positive relationship, with only a modest decline among the largest firms (in both panels). Overall, the positive association between firm size and women’s employment is robust to firm unobservables and to industry and location controls, and it persists under alternative measures of firm size such as output (Appendix Table A.2).

We further assess robustness in two specifications. First, using an extensive-margin outcome—an indicator for whether the firm employs any female worker—we again find a statistically significant positive relationship between firm size and the likelihood of employing women.<sup>21</sup> Second, we replace log firm size with size categories to flexibly capture nonlinearity (Appendix Table A.3). The female share rises monotonically with firm size, but the incremental gains diminish at higher size bins.<sup>22</sup>

### 3.1.2 Alternate Firm-Level Data: Economic Census

We next examine whether the positive relationship between firm size and proportion of hired female employees holds up using the Economic Census of firms in India, which reports employment data for both registered and unregistered establishments across *all* industries.

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<sup>21</sup>We find a one percent increase in employment (output) raises the probability that the firm employs a female worker by 0.07 percentage points (0.017 percentage points). Estimates are omitted for brevity but available on request.

<sup>22</sup>Relative to firms with 1–5 workers, the female share is higher by 0.052 (43 percent of the mean) in firms with 10–25 workers and by 0.113 (94 percent of the mean) in firms with > 300 workers.

However, this data is only collected once every seven years (1998, 2005, 2013) and does not provide identifiers to track the same enterprise over time. It collects information on hired workers and all employees of an enterprise by gender, the owner’s gender, the organization type, detailed industry classification, and district of location.<sup>23</sup> We include industry-by-year and district-by-year fixed effects to absorb time-varying differences in female employment across industrial sectors and locations.

Appendix Table A.4 reports analogous estimates using the Economic Census: proportion of hired female workers increase by 0.028 (column 5), when firm size increases by 1 percent—implying an elasticity of 0.18—closely matching the ASI estimate.<sup>24</sup> The non-linear specification (column 6) indicates that this relationship is positive over the range of firm sizes that accounts for most observations. We conduct additional checks. Appendix Table A.5 shows that larger size categories employ a higher female share. Appendix Table A.6 documents similar patterns across rural and urban areas within four broad industrial sectors—agriculture, manufacturing, construction, and services.

Finally, we examine heterogeneity by owner gender (which is unavailable in the ASI). About 8 percent of enterprises are female-owned, and these firms employ substantially higher female shares—roughly 50–70 percent of hired workers on average (Appendix Table A.7).<sup>25</sup> Appendix Table A.7 shows that the positive size–female share gradient is driven primarily by male-owned firms (Panel A). For female-owned firms (Panel B), patterns vary by sector: agriculture displays an initial dip followed by an increase, while other sectors exhibit a decline with a flattening at larger sizes, yielding a U-shape overall.<sup>26</sup> Since 92 percent of enterprises

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<sup>23</sup>Industry is defined at the most granular NIC available in each round: 4-digit in 1998 and 2005, and 3-digit in 2013.

<sup>24</sup>Columns (1)–(4) use the proportion of women among all workers (hired workers+unpaid family members), while columns (5)–(6) use the proportion among hired workers, the latter being comparable to the ASI hired-worker measure and therefore our preferred outcome.

<sup>25</sup>Differences in levels may reflect lower discrimination, provision of women-valued amenities, and sectoral sorting of female-owned firms. For instance, Economic Census data indicate that female-owned manufacturing enterprises are concentrated in a small set of industries (e.g., tobacco products (accounts for almost 50 percent), textiles, and matchsticks), whereas male-owned enterprises are more dispersed across manufacturing.

<sup>26</sup>This is consistent with the model in Appendix B: if female-owned firms provide certain amenities even at small scale, the interaction of amenity provision, task composition, and discrimination as firms grow can generate non-monotonicity.

are male-owned in 1998–2013, the aggregate relationship remains positive, underscoring the joint importance of firm size and owner gender for women’s employment (Chiplunkar & Goldberg, 2024).

## 3.2 Individual Level Data

We use repeated cross-sections from India’s National Sample Survey (NSS) Employment and Unemployment Schedules (EUS) for 1999–00, 2004–05, 2009–10, and 2011–12 (henceforth 1999, 2004, 2009, and 2011), and the Periodic Labour Force Surveys (PLFS) for 2017–18 and 2018–19 (2017 and 2018).<sup>27</sup> Each round spans July of the first year to June of the second, covering a full year.<sup>28</sup> Both surveys use a two-stage stratified sampling design, yielding nationally representative household cross-sections.

The surveys collect detailed individual information on age, gender, education, marital status, employment, earnings, and the industry and occupation of employed workers.<sup>29</sup> For non-farm employment, they also record enterprise size, full- versus part-time status, and access to social security benefits. Firm size is measured in coarse bins: less than 6, 6–9, 10–19, and 20+ workers, rather than the continuous measures available in the ASI. Our analysis sample comprises paid employees aged 15–65 at the time of the survey.

Appendix Table A.8 summarizes key variables in the individual-level data. Women constitute 19 percent of paid workers. About 60 percent of workers are employed in firms with ten or fewer employees, underscoring the central role of micro and small firms in Indian labor market.

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<sup>27</sup>We exclude the 2007 NSS round because it does not collect firm-size information.

<sup>28</sup>The PLFS replaced the NSS EUS in 2017 and remains largely comparable in design and variables. A minor difference is that the PLFS additionally stratifies households in villages and urban blocks by members’ general education; this does not affect population estimates because all analyses use survey weights.

<sup>29</sup>Our main employment measure is based on the Usual Principal Activity Status over the 365 days preceding the survey: an individual is classified as employed if she or he worked at least 30 days during this period. We use this annual reference because firm-size information is collected for employment recorded under this definition.

### 3.2.1 Findings: Individual Level

Using data for employed individuals, in the non-farm sector, Table 2 reports whether the probability of being a female worker changes with firm size (Equation C.2). Columns (1)–(2) pool full-time and part-time workers; column (1) includes industry-by-year and occupation-by-year fixed effects, while column (2) adds a stricter set of controls that absorb within-industry differences across occupations in women’s employment. In both specifications, the probability that a worker is female increases with firm size. Relative to firms with 1–5 workers, firms with 10–20 workers and 20+ workers have a 1.9 percentage point (10 percent of the mean) and 4.1 percentage point (22 percent of the mean) higher female share, respectively (column 2). Columns (3)–(4) restrict the sample to full-time workers and yield similar patterns: women are 12.5 percent and 28 percent more likely to be employed full-time in firms with 10–20 and 20+ workers, respectively, than in firms with 1–5 workers (column 4). The size gradient is thus somewhat stronger for full-time employment.

**Other evidence:** To gauge whether this relationship between firm size and relative female employment is specific to India, we also conduct a similar exercise in the U.S. We use individual data from the nationally representative Annual Social and Economic (ASEC) Supplement of the Current Population Survey (CPS), U.S.A. for the years 2000-2021 and study the relationship between the gender of the respondent and the size of the firm that they work for. As illustrated in Table A.9 in the Appendix, we find that female employees are more likely to work in larger firms, a pattern which closely mirrors our findings in India.

Overall, the results presented above show that women are disproportionately employed in larger firms. This result is consistent across firm and individual-level data and is robust to firm fixed effects and to controls for occupation and task-related variation in women’s employment. We next examine whether regulatory reforms that encourage firm growth by reducing compliance burdens also increase women’s employment. If larger, more productive

firms employ relatively more women, such reforms should raise the female share of paid employment.

## 4 Impact of Labor Law Amendments

Regulatory requirements under the labor laws are often regarded as one of the hurdles for manufacturing sector growth in India. The key labor regulations affecting the sector are anchored under the Factories Act, the Industrial Disputes Act and the Contract Labor Act.

The Factories Act applies to manufacturing establishments above statutory employment thresholds: historically, ten or more workers if the factory uses electric power and twenty otherwise. Its provisions primarily regulate working conditions, including standards for worker health (cleanliness, waste disposal, ventilation, temperature, lighting, and congestion), worker safety (fire precautions and safeguards against machinery and chemical hazards), hours of work with overtime premiums, and paid annual leave. The main gender-specific provision relates to creches, which becomes binding once female employment exceeds 30.<sup>30</sup> [Amirapu and Gechter \(2020\)](#) estimate that compliance with these regulations raises unit labor costs by roughly 35 percent, generating incentives for firms to remain below the relevant thresholds.

The Industrial Disputes Act (IDA) requires industrial establishments above a statutory employment threshold to obtain prior state government approval before retrenching workers.<sup>31</sup> Existing evidence suggests that the IDA, by limiting firms' ability to adjust employment in response to adverse shocks, contributes to the prevalence of small firms in India ([Hsieh & Olken, 2014](#)).<sup>32</sup>

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<sup>30</sup>Certain requirements apply only to larger establishments. For example, factories with more than 250 workers must provide a canteen and separate toilets, with toilet capacity aligned to the gender composition of the workforce. Factories with more than 150 workers must provide adequate shelters and a lunchroom with drinking water.

<sup>31</sup>The threshold was typically 100 workers in most states until 2013. At this threshold, [Amirapu and Gechter \(2020\)](#) find smaller increases in unit labor costs than at the 10-worker threshold. Retrenched workers are entitled to compensation equal to 15 days' average pay per year of service. For layoffs, workers receive 50 percent of their basic wages plus dearness allowance for each day of layoff (up to 45 days). The Act also mandates prior notice of 60 days under Chapter V-A and 90 days under Chapter V-B.

<sup>32</sup>See also [The Economist](#). Some studies document limited bunching at the 100-worker threshold and

The Contract Labor Act (CLA) governs firms’ use of contract workers, primarily to prevent exploitation. It typically applies to establishments employing 20 or more contract laborers and sets minimum standards for working conditions, including wages and safety.<sup>33</sup> At the same time, contract labor provides firms with adjustment margins and has been linked to higher productivity (Hirsch & Mueller, 2012). Relaxing thresholds for engaging contract workers may therefore increase flexibility while reducing compliance costs.

More broadly, punitive labor regulation has been shown to reduce output and employment (Aghion et al., 2008; Besley & Burgess, 2004) and to constrain firm growth (Almeida & Carneiro, 2009). As firms expand, the likelihood of inadvertent noncompliance rises; when even minor violations carry criminal penalties, managers may rationally limit scale to reduce inspection risk. Criminal liability can also increase non-productive costs. For instance, through inspector bribes during inspections and lengthy dispute resolution, thereby strengthening incentives to remain small.

## 4.1 Amendments to Labor Laws

States can amend these statutes. Recent reforms have typically raised applicability thresholds: for the Factories Act, from 10 to 20 workers in power-using establishments and from 20 to 40 in non-power establishments; for the IDA, from 100 to 300 workers for layoffs and closures without prior approval; and for the CLA, from 20 to 50 contract workers. Several states have also decriminalized violations under these Acts, thus reducing the punitive nature of enforcement and potential inspector harassment. If these regulations constrain firms from reaching efficient scale, such relaxations should promote firm growth.

We exploit cross-state variation in these amendments to the Factories Act, the IDA, and the CLA, including decriminalization, between 2009 and 2019. Five states implemented these

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argue that the regulation may not bind. However, Padmakumar (2021) notes that the absence of bunching need not imply weak distortions: if establishment transitions around the threshold respond when the policy is relaxed, the regulation may still constrain firm growth.

<sup>33</sup>Contract workers do not ordinarily count toward the IDA employment threshold; however, if a court deems a contracting arrangement a sham and treats contract workers as employees of the principal employer, the employer may be penalized. See [Bombay High Court judgment](#).

reforms: Rajasthan (2014-15), Madhya Pradesh (2015-16), Maharashtra (2016-), Jharkhand (2017-18), and Uttar Pradesh (2018-19).<sup>34</sup> Rajasthan and Jharkhand amended all three Acts. Maharashtra amended the Factories Act in 2015 (effective February 2016) and subsequently amended the CLA and IDA (effective January 2017 and June 2017, respectively); we therefore code Maharashtra as treated from 2016-17 onward. Uttar Pradesh amended the Factories Act and CLA in 2017, with implementation from 2018; it had already adopted the 300-worker IDA threshold in 1950. Madhya Pradesh also amended the IDA in 2015.<sup>35</sup>

Alongside these statutory changes, Rajasthan also tightened rules around unionization. Rajasthan, Jharkhand, and Maharashtra made violations under the Factories Act non-punishable by arrest upon payment of a fine. In addition, post-amendment, courts could not take cognizance of complaints alleging violations against employers without prior written permission from the state government. Several states also introduced statutory time limits for raising disputes, with the stated objective of reducing litigation.<sup>36</sup> Many states further increased permissible overtime hours.<sup>37</sup>

Taken together, these reforms reduced the expected costs of non-compliance with these Acts while directly relaxing size-based regulatory burdens. Establishments below 100 workers could scale beyond the 20-, 40-, and 100-worker thresholds at lower compliance cost, and establishments with 100–300 workers gained greater flexibility in hiring and retrenchment. Firms above 300 workers primarily benefit through decriminalization and general-equilibrium

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<sup>34</sup>The years refer to the financial years in India (April of previous year to March of next year), since ASI captures firm outcomes in a given financial year. Some states simultaneously increased severance pay and extended notice periods (e.g., from one to three months), which are relatively pro-worker changes (Bhattacharjea, 2021).

<sup>35</sup>Jharkhand amended the Factories Act in 2015, but implementation occurred in December 2016, and amended the IDA in 2016 with implementation in 2017; we thus code Jharkhand as treated from 2017. Madhya Pradesh, Uttar Pradesh, and Maharashtra also amended the Factories Act to permit women to work night shifts; we assess robustness by excluding these states, since night-shift liberalization may directly affect female employment. We also exclude the north-eastern states (including Assam) due to small sample sizes. Our main analysis sample comprises 26 states and union territories.

<sup>36</sup>Rajasthan also amended the Apprentices Act, 1961, fixing apprentice stipends at the minimum wage and shifting part of training costs to the government.

<sup>37</sup>Uttar Pradesh also raised the threshold from 50 to 100 workers for exemptions from overtime-related regulations.

gains if smaller firms expand output.<sup>38</sup>

If these amendments increased firm size and larger firms employ a higher female share, female employment should rise in reform states. We next test this implication empirically.

## 4.2 Empirical Strategy

We estimate the causal effect of these amendments on firm outcomes using ASI data from 2009–2019<sup>39</sup> and a difference-in-differences design. Specifically, we compare changes in outcomes in reform states relative to non-reform states before and after the amendments, controlling for time-invariant firm heterogeneity:

$$Y_{ijst} = \delta_i + \delta_t + \delta_{jt} + \beta_1 \text{Amendment}_{st} + \epsilon_{ijst}, \quad (11)$$

where  $Y_{ijst}$  denotes the outcome for firm  $i$  in industry  $j$  in state  $s$  and year  $t$ . Main outcomes include the female share of manufacturing workers and firm-size measures such as log of employees and output.  $\text{Amendment}_{st}$  equals one for treated states in post-reform years and zero otherwise. We include firm fixed effects ( $\delta_i$ ), year fixed effects ( $\delta_t$ ), and industry-by-year fixed effects ( $\delta_{jt}$ ) to absorb time-varying shocks and policies common within industries. Standard errors are clustered at the state level, the treatment unit. Given the limited number of clusters (26 states and union territories), we also report state-clustered wild bootstrap inference. The coefficient  $\beta_1$  captures the average effect of the amendments on firm outcomes.

Because treatment timing is staggered across states, the two-way fixed effects (TWFE) estimator may be biased (Goodman-Bacon, 2021). We therefore complement TWFE estimates with the estimator proposed by Callaway and Sant’Anna (2021), which accommodates

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<sup>38</sup>Although the reforms should increase growth incentives below 300 workers, firms near the 300-worker threshold could also adjust downward to preserve flexibility.

<sup>39</sup>We focus on 2009–2019 because ASI variable definitions, and industry and product codes are consistent after 2008. Moreover, the 2005–2008 period coincides with staggered adoption of a new indirect tax regime (VAT), which affected firm outcomes (Agrawal & Zimmermann, 2025). Our results are robust to including earlier ASI years.

staggered adoption and permits wild cluster bootstrap standard errors.<sup>40</sup>

Finally, we estimate dynamic treatment effects using an event-study specification to assess pre-trends:

$$Y_{ijst} = \delta_i + \delta_t + \delta_{jt} + \sum_{\tau=-4, \tau \neq -1}^2 \beta_{\tau} \text{Amendment}_s^{\tau} + \epsilon_{ijst}, \quad (12)$$

where  $\text{Amendment}_s^{\tau}$  equals one for treated states at event time  $\tau$  relative to the reform year and zero otherwise. We bin endpoints at  $\tau = -4$  and  $\tau = 2$  and normalize coefficients to  $\tau = -1$ .<sup>41</sup> The year of the amendment is denoted as event time 0. The coefficients  $\beta_{\tau}$  trace outcomes relative to the year before reform and provide a direct test of parallel pre-trends. If the amendments raise the female share of employment, we should observe  $\beta_{\tau} > 0$  for  $\tau \geq 0$ .

Appendix Table A.10 compares treated and control states using pre-reform data from 2009–2014. Firm size, measured by total employees, is statistically indistinguishable across the two groups, suggesting that smaller firm size did not drive the decision to amend the Acts.<sup>42</sup> Average output, however, is slightly higher in treated states, plausibly reflecting differences in industrial composition. Food processing and textiles account for about 36 percent of manufacturing units in control states but only 26 percent in treated states, which have a larger share of metals, electrical goods, and transport-related manufacturing. The latter set of industries are more capital intensive and typically employ fewer women, partly accounting for the lower female share in treated states.<sup>43</sup> A further explanation is that most treated states are in North India, where female labor supply has historically been lower due to social norms (Dyson & Moore, 1983). Because the amendments did not explicitly target female employment, it is unlikely that reforms were chosen in response to the female

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<sup>40</sup>We also implemented the approach of Sun and Abraham (2021) and obtain similar results; we omit these for brevity. We estimate TWFE without sampling weights to ensure comparability with the Callaway and Sant’Anna (2021) event-study framework, which does not incorporate sampling weights; weighted TWFE estimates are similar.

<sup>41</sup>The first reform occurs in 2014 and the last in 2018, implying up to six post-reform and up to eight pre-reform periods in the data. Binning at  $-4$  and  $2$  maximizes the number of treated states contributing to the event window (Schmidheiny & Siegloch, 2019).

<sup>42</sup>Several states undertook reforms after the pandemic to promote a more business-friendly environment amid slower growth.

<sup>43</sup>The raw gap in the female employment share is 9 percentage points; adjusting for industrial composition reduces it to 6.5 percentage points.

employment share. In the next section, we show that female employment trends were similar across treated and control states prior to reform. Nonetheless, we also assess robustness using a matching estimator.

### 4.3 Impact of Amendments

Table 3 reports TWFE difference-in-differences estimates from Equation 11. Columns (1)–(2) show that the amendments increase the female share of employment by about 0.004 (roughly 4 percent of the mean) once we include firm and industry-by-year fixed effects (column 2). Because we have fewer than 30 clusters, we report wild cluster bootstrap p-values (in brackets) and find the effect is marginally significant at the 15 percent level. Figure A.6, panel (a), plots the corresponding event-study coefficients: pre-amendment trends are similar across treated and control states, while the female share rises starting in the year the amendments take effect.

A natural mechanism for the observed increase in share of female workers is firm growth induced by higher regulatory thresholds. To examine this, we estimate the impact of the amendments on various firm size measures. Columns (3)–(4) of Table 3 show increases of 5.4 percent in total employees and 19 percent in output after the amendments. Figure A.6, panels (b)–(c), confirms positive post-amendment effects; output is significant at the 10 percent level and employment at the 15 percent level using clustered wild bootstrap inference. However, these TWFE event studies exhibit slight pre-trends in firm-size outcomes.

Since TWFE estimates can be biased under staggered adoption, we re-estimate dynamic effects using the Callaway and Sant’Anna (2021) estimator, using never-treated states as the control group. Figure 2 shows no evidence of differential pre-trends and a clear post-amendment increase in the female share (panel a), employees (panel b), and output (panel c).<sup>44</sup> The estimated ATT implies a 0.005 increase in the female share (about 5 percent of the mean), significant at the 5 percent level. Employment rises by 4 percent (significant at the

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<sup>44</sup>If anything, treated states display slightly declining relative trends prior to reform.

15 percent level) and output by 13 percent (significant at the 10 percent level), with state-clustered wild bootstrap standard errors. Overall, accounting for staggered implementation, the amendments increased firm size and the female share of employment.<sup>45</sup> These results indicate that growth-oriented regulatory reforms can also raise female employment.

### 4.3.1 Robustness

We check the robustness of our estimates to the following alternative specifications:

**Matching:** To address concerns that our post-treatment effects are driven by differential pre-trends, we implement the Synthetic Difference-in-Differences (SDID) estimator of [Arkhangelsky et al. \(2021\)](#), which combines the Synthetic Control approach ([Abadie, Diamond, & and, 2010](#)) with a DID-style comparison. Rather than assuming parallel trends, SDID constructs a reweighted control group that matches treated units in the pre-period.<sup>46</sup> Because SDID requires a balanced panel, we aggregate the ASI unbalanced firm-panel to a state-by-year panel by averaging outcomes within each state-year. SDID then forms a synthetic control using unit and time weights. Unlike TWFE event studies, SDID does not normalize to a base event time; the dynamic effect at each date is the level difference between the treated group and its synthetic control. Appendix Figure [A.7](#) plots SDID estimates for the female share of employment (panel a) and firm-size measures (panels b–c), accounting for staggered adoption. We report cluster-bootstrapped standard errors. Pre-treatment estimates are indistinguishable from zero, while post-amendment outcomes rise: the female share increases by about 3.5 percent of the mean and total employment by roughly 6 percent. Although the patterns are consistent with our firm-level results, the state-level SDID estimates are less precise due to state-level aggregation.

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<sup>45</sup>We also estimate a roughly 20 percent increase in raw materials, while capital expenditure rises by about 2.2 percent and is statistically insignificant, suggesting expansion primarily through labor and intermediate inputs rather than capital deepening.

<sup>46</sup>Relative to standard synthetic control, SDID uses a dual reweighting scheme: it first chooses unit weights to balance treated and control outcomes in pre-treatment periods, and then chooses time weights that emphasize the subset of pre-treatment periods most predictive of post-treatment outcomes. This procedure improves pre-period fit and can reduce bias when untreated units exhibit differential trends.

**Alternative female employment measures:** We next assess robustness to alternative measures of female employment. Appendix Table A.11 reports staggered DID estimates for: an extensive-margin indicator for whether a firm employs any woman (column 1); log female and log male workers (columns 2–3); and the female share of mandays (column 4). The amendments raise the probability that a firm employs a woman by 1.3 percentage points (about 5 percent relative to a baseline of 28 percent firms employing any female worker). The increase in the female share is driven by a larger rise in female than male employment, and the female manday share increases by 5 percent of the mean.

**Other checks:** First, we drop treated states one at a time to verify that no single state drives the results. Appendix Figure A.8 shows that the post-reform increases in the female share (panel a), employment (panel b), and output (panel c) remain robust. Second, we extend the sample to 2001–2019 (Appendix Table A.12, Panel A) and obtain similar estimates. Finally, we exclude treated states that also liberalized night-shift work for women (Panel B). The increase in the female share persists; output rises by 16 percent, while the employment effect remains comparable in magnitude but becomes less precisely estimated as the sample size falls.

### 4.3.2 Ruling out Alternative Channels

We test several alternative channels, apart from increase in firm size, that could potentially increase female share of workers after the reforms. First, the reforms could increase labor demand through greater entry and reduced exit in treated states, raising demand for women. We find a positive but imprecise effect on the number of firms per state in a given industry after the amendments (Appendix Table A.13).

Second, we examine whether firms began exporting after the amendments since existing literature shows that exporting firms are more likely to hire female labor. Appendix Table A.14 shows that there was no increase in export share or the probability of exporting by firms

after the reforms (columns 1–2).

Third, firms might substitute away from contract labor toward permanent workers if dismissals become easier, potentially changing gender composition if women are less represented among contract workers. Columns 3–4 of Appendix Table [A.14](#) show no decline in contract labor use.

Fourth, the amendments may raise turnover by easing retrenchment restrictions, allowing firms to replace incumbents with younger hires. If women are more represented among younger job seekers, this could increase the female share. This channel is less relevant for firms with fewer than 100 employees, which already faced limited constraints on firing. We therefore examine heterogeneity by pre-treatment firm size (defined as pre-2014 for control states and pre-reform years for treated states). Appendix Table [A.15](#) shows that firms below 100 employees increase the female share by 0.4 percentage points (4 percent of the mean), significant at 5 percent. The increase is larger for firms with 100–300 employees (0.6 percentage points; 5 percent of the mean). Firms above 300 show the smallest and statistically insignificant increase in female share, and no meaningful expansion in employment (with smaller output gains). This pattern is consistent with the reforms lowering compliance costs most strongly for firms below 300 employees.

Finally, reduced union power could matter if male-dominated unions impeded women’s entry. Only Rajasthan amended rules affecting unionization, and our results are robust to dropping Rajasthan, making this channel unlikely. Moreover, union density in India is low (about 6.3 percent) ([Labour Bureau, 2020](#)), unions are historically more concentrated in larger firms ([Pal, 2008](#)), and the strongest effects in our data are concentrated among small and medium firms. If anything, scale expansion could increase unionization rather than reduce it.

Taken together, these findings show that firm size growth relative to other channels is likely the most important channel behind the observed positive effects of the amendments on the proportion of female workers.

## 5 Mechanisms

This section examines mechanisms underlying the positive relationship between the female employment share and firm size. As discussed in Section 2, three channels may account for this pattern: (i) larger firms provide amenities that women value relatively more, (ii) gender discrimination is lower in larger firms, and (iii) task requirements shift with firm size in ways that raise demand for women.

Evidence from the individual-level data (Table 2) shows that the relationship persists after controlling for occupation within industry, suggesting that task composition alone cannot explain our findings. Moreover, the ASI results focus on manufacturing workers, among whom task variation with firm size is likely limited. Related work on exporting firms instead emphasizes increased demand for women in non-production tasks (Banerjee et al., 2022; Bonfiglioli & De Pace, 2021). We therefore focus on the remaining two channels below.

### 5.1 Amenities: Descriptive Evidence

We first assess whether women sort into jobs with better amenities and whether larger firms are more likely to provide them.

#### 5.1.1 Do women value amenities differently?

We use individual-level survey data that records job attributes such as part-time status, written contracts, maternity/health benefits, pensions, and paid leave. These amenities may be differentially valued by gender. For example, if women prefer part-time work or maternity benefits, and larger firms disproportionately provide these amenities, this could contribute to the observed size gradient.

We begin with a revealed-preference test: conditional on observed characteristics, if women are more likely than men to work in jobs with a given attribute, this is consistent with higher valuation of that attribute. Table 4 relates these job amenities to the probability

that a worker is female. The dependent variable is whether a worker is a female and the main explanatory variables are job amenities; other job attributes are included as controls. Columns (1) and (2) progressively add industry-by-year and occupation controls, along with individual covariates and the full set of amenities. Women are 17 percentage points more likely to work part-time, 2.7 percentage points (14 percent of mean) more likely to have a written contract, and 2 percentage points (about 11 percent of mean) more likely to hold jobs offering healthcare and maternity benefits. By contrast, old-age support is negatively associated with female employment, which could occur if men value investment for old-age support relatively more while women value in-hand cash.<sup>47</sup>

These patterns align with prior evidence that women place greater weight on amenities such as flexibility, stability, remote work, safe transport, safe workplaces, and childcare (Baker, Gruber, & Milligan, 2008; Garlick, Field, & Vyborny, 2025; Mas & Pallais, 2017; Wiswall & Zafar, 2018) relative to men relative to benefits like pension (Schuetz, 2026). Evidence also shows that women in developing countries are more likely to prefer home-based work (Ho, Jalota, & Karandikar, 2024), childcare (Bjorvatn et al., 2025), and safe transport (Garlick et al., 2025).

### 5.1.2 Do larger firms provide better amenities?

Table 5 examines how amenities vary with firm size. Column (1) shows that part-time work does not increase with firm size, ruling it out as a primary explanation. In contrast, larger firms are substantially more likely to offer formalization and benefits. Workers in firms with 20 or more employees are 14 percentage points (about 50 percent) more likely to have a written contract (column 2). Firms with 6–10, 10–20, and more than 20 employees are 1.6, 4.7, and 15 percentage points (about 70 percent) more likely to offer healthcare and maternity benefits (column 3). Larger firms are also more likely to offer pensions (column 4) and paid leave (column 5), with increases of roughly 70 percent and 45 percent, respectively. Thus, we

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<sup>47</sup>The sample is smaller because part-time status is available only in the NSS rounds. Columns (3) and (4) drop the part-time variable and use the full sample; results are similar.

find that most amenities captured in the survey data, except part-time work, increase with firm size.

We complement this evidence using employee-reported benefits from *AmbitionBox*, a large Indian aggregator that collects crowd-sourced information on workplace benefits. Appendix Table A.16 shows that firms with more employees are more likely to offer childcare, free transport, and work-from-home options, among other amenities. A firm with at least 500 employees is nearly 40 percentage points more likely to offer these benefits than a firm with at most 10 employees—approximately a 100 percent increase for childcare and 60 percent for transport. These amenities are also documented to be particularly valued by women (Mas & Pallais, 2017; Wiswall & Zafar, 2018). Together, these results indicate that larger firms offer better amenities along dimensions likely to matter for female labor supply.

While ASI does not record specific amenities provided by a firm, it captures total employer welfare expenditures (including spending on maternity benefits, creches, canteens, educational/cultural/recreational facilities) and employer contributions to old-age benefits such as provident fund (PF). We deflate these expenditures using the CPI (base year 2004). Appendix Table A.17 relates log per-employee welfare and PF spending to firm size (total employees), exploiting within-firm variation over time. We find that a one percent increase in employment is associated with an increase in welfare spending per employee by 0.42 percent and pension-related spending per employee by 0.38 percent (Panel A, columns 1–2). Cross-sectional estimates (Panel B) show similar positive gradients. Thus, even in administrative data that does not enumerate specific amenities, larger firms spend more on worker welfare.

The model in Section 2 predicts that higher productivity and profits enable bigger firms to bear the fixed costs of amenities. Consistent with this mechanism, Appendix Table A.17 shows a positive association between firm size and productivity measures. We deflate profits using two-digit industry-specific WPI (base year 2004) and define labor productivity as real output per employee. Larger firms have higher profits per employee and higher labor productivity in both panel and cross-sectional specifications: within firms, a 1 percent increase

in size is associated with a 1 percent increase in profits and a 0.58 percent increase in labor productivity (Panel A, columns 4–5). These patterns suggest that larger, more profitable firms are better positioned to finance amenities.

## 5.2 Amenities: Impact of Labor Law Amendments

Next, we examine the effect of the labor law amendments on welfare expenditure and firm productivity. Because the amendments raised the size thresholds for coverage under the Factories Act, they reduced the set of firms subject to statutory health and safety provisions. If such amenities are valued relatively more by women, this could, in principle, lower the female employment share. However, by enabling firms to grow, the reforms may allow firms to choose amenity investments optimally to attract workers, rather than relying on externally imposed compliance that can invite harassment and raise costs ([Amirapu & Gechter, 2020](#)).

If female employment rises because growing firms provide amenities that women value, welfare expenditure per employee should increase. Appendix Table [A.18](#) shows that welfare expenditure per employee rises by 10 percent after the amendments (column 1). The effect on provident fund (PF) spending is positive but imprecise (about 9 percent). Profits per employee and output per employee increase by 6.6 percent (columns 4–5). Figure [3](#) reports event-study estimates using the staggered design: welfare spending per employee increases (about 5 percent), profits per employee rise (about 9 percent), and labor productivity increases by 5.3 percent. While the estimates are noisy, the dynamics suggest that productivity responds with a lag.

These results are consistent with an amendment-induced increase in firm size accompanied by higher amenity/welfare provision, which may have contributed to the rise in female employment documented in Section [4](#). The gains in output and profits may reflect both lower compliance costs and scale expansion.

### 5.3 Discrimination

A second potential explanation for the higher female employment share in larger firms is lower discrimination. One suggestive, albeit imperfect, test is whether the gender wage gap varies with firm size. Interpreting such patterns is non-trivial because worker composition can differ across firms (Brown & Medoff, 1989; Eeckhout, 2018). For instance, if higher-ability women disproportionately sort into bigger firms, the observed gap may be smaller in bigger firms even in the absence of changes in discriminatory behavior. Moreover, amenities can raise women’s marginal productivity (see discussion in Section 2), which would also compress the gap. Conversely, if women value amenities more, firms may partly offset these benefits through lower wages for women via compensating differentials. Thus, the wage-gap gradient with respect to firm size is theoretically ambiguous.

We examine this relationship using the NSS and PLFS individual data in Table A.19, where the dependent variable is the log daily wage.<sup>48</sup> Columns (1)–(2) show the expected positive association between wages and firm size. Columns (3)–(4) interact firm-size categories with gender to assess whether the gender wage gap differs by firm size. The estimates indicate that the gap is smaller in larger firms: on average, women earn about 42 percent less than men, but the gap is roughly 36 percent in firms with 6–20 workers and about 30 percent in firms with 20+ workers. While we control for observable characteristics (age, education, caste, religion, sector, and marital status) and include rich fixed effects, these controls may not fully address selection on unobserved ability.

Importantly, we do not find evidence that the gender wage gap widens with firm size. This pattern is consistent with (but does not establish) either lower discrimination in larger firms or stronger selection of higher-ability women into such firms dominating the compensating-differential channel.<sup>49</sup> We also do not find robust effects of the amendments on the gender

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<sup>48</sup>Daily wages are constructed by dividing weekly earnings by the number of days worked in the preceding week.

<sup>49</sup>Using firm-level ASI outcomes, Table A.17, column (3), relates the log female-to-male wage ratio to firm size. The coefficients are small and statistically insignificant in both within-firm and cross-sectional specifications.

wage gap (Figure 3, panel (c)), nor do we detect a clear effect on average wages paid by firms.<sup>50</sup>

Overall, the wage evidence is consistent with the possibility that discrimination declines with firm size, but it is also consistent with compositional changes and productivity effects operating through amenities.

Finally, we conduct a resume audit study to assess whether hiring responses differ by applicant gender and whether any such differences vary with firm size (details in Appendix D). We sent two fictitious resumes—one male and one female—matched on qualifications and experience (3 years) and held constant on location (Delhi), age, and marital status (married), across four roles (BPO, Finance, HR, and Sales/Marketing) during June–August 2024. Applications were submitted via a major online job portal on weekdays at consistent times, with the gender of the profile randomized by day and sent on consecutive weekdays. We proxy firm size using employee counts from *AmbitionBox*; in the final sample, 497 firms have 1–50 employees, 1,316 have 51–200, and 2,806 have more than 200 employees. We record callbacks received via phone, email, or the platform and estimate whether callback differentials vary by applicant gender and firm size.

Appendix Table D.2 reports overall and role-specific callback differences. We find lower callback rates for female profiles, concentrated in more male-typed roles such as finance and sales/marketing, consistent with the broader audit-study literature (Baert, 2018). Appendix Table D.3 examines heterogeneity by firm size. We do not find systematic evidence that larger firms discriminate less in callbacks.

Two caveats are important. First, the audit study pertains to online hiring for service-sector jobs and may not map directly to manufacturing recruitment or to hiring that occurs through informal networks. Second, callback differentials capture an early stage of hiring and may not reflect wage setting, workplace treatment, or retention. With these limitations in mind, while the audit study evidence does not support lower discrimination by larger

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<sup>50</sup>We do not find a significant effect of the amendments on overall wage rates paid by firms.

employers, these are only suggestive in nature and future work in this area is required to corroborate the results in broader settings.

## 6 Conclusion

Using firm-level panel data and individual-level survey data, we find that the female employment share increases with firm size in India. This relationship holds after controlling for firm fixed effects, industrial structure, firm location, and occupation-by-industry variation in gender composition. To estimate causal effects, we exploit quasi-exogenous variation from state-level labor law amendments that raised firm-size thresholds for regulatory applicability and implement a staggered difference-in-differences design. The amendments increase firm size by about 5 percent and the share of hired female workers by about 4 percent.

Guided by a simple framework, we argue that larger, more productive firms are more likely to provide workplace amenities that are valued relatively more by women. These amenities raise women’s productivity and willingness to work, helping explain the positive firm-size gradient in female employment. Consistent with this mechanism, we show that larger firms are more likely to offer maternity benefits, childcare, work-from-home arrangements, employer-provided transport, and greater job stability (formal contracts). Women are also more likely to hold jobs with these amenities in our data. We further find that welfare expenditure per employee rises in treated states relative to control states following the amendments. Taken together, the evidence suggests that policies that facilitate firm growth can increase female employment by enabling firms to invest in amenities that attract and retain women. We also do not find a higher gender wage gap in larger firms, suggesting that compensating differentials are not the dominant force. Finally, we present suggestive evidence showing that task-based explanations and discrimination are unlikely to be the primary channels behind our findings.

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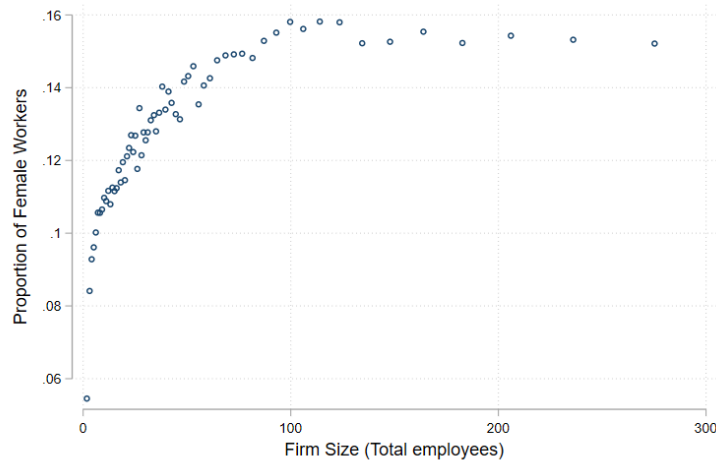
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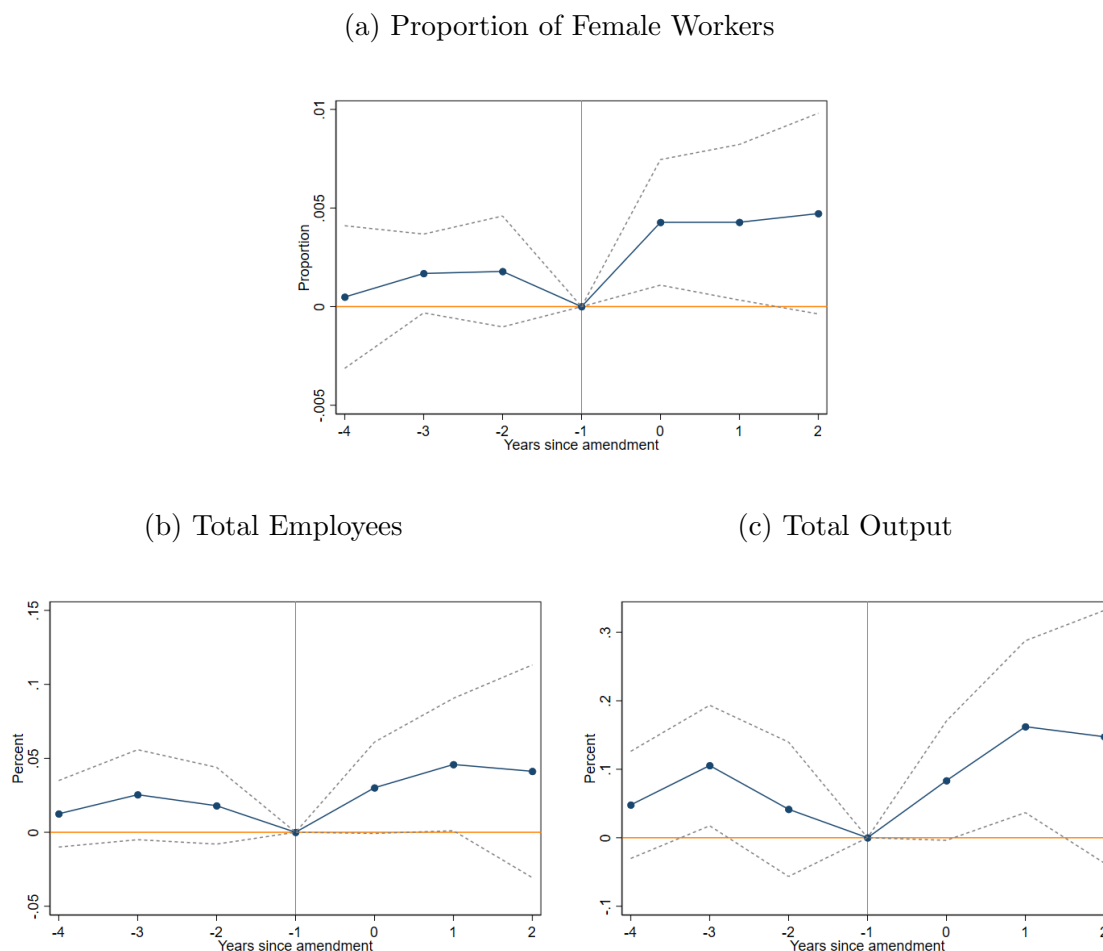
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Figure 1: Proportion of Female Workers across Firm Size (ASI data)



*Notes:* The figure plots the binscatter between the proportion of female workers and total employees in a firm.  
*Source:* ASI 1998-2019.

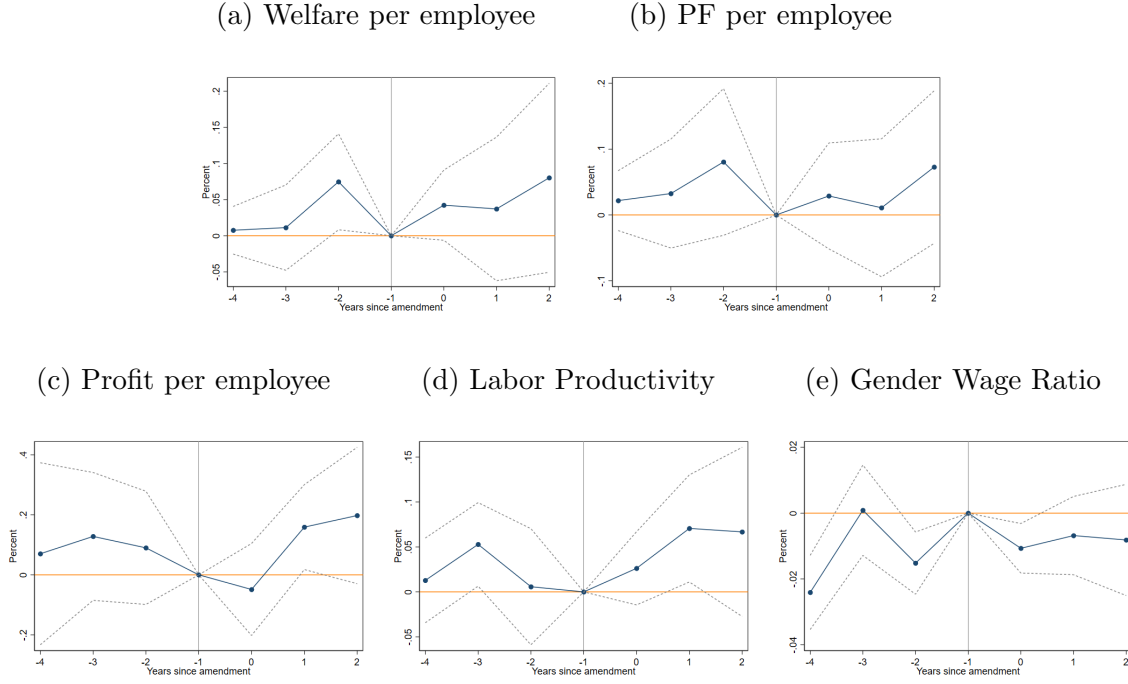
Figure 2: Impact of Amendments on Female Employment and Firm Size (Staggered Event Study)



*Notes:* The above figures show event-study plots estimating the impact of state-level labor law amendments using the (Callaway & Sant'Anna, 2021) estimator. The outcome of interest is the proportion of female workers (Panel a), (logged) number of total employees (Panel b) and (logged) total value of output (Panel c). The unit of observation is the manufacturing establishment in a year. We keep establishments that report using some labor in a given year. The solid line represents the average annual treatment effects, and the dashed lines denote the 95% confidence intervals. The treatment effects are with respect to the year before the amendment came into force (dashed vertical line). Specifications include establishment and year fixed effects. Standard errors are wild-bootstrapped and clustered by state.

*Source:* ASI 2009-2019.

Figure 3: Impact of Amendments on Other Firm Outcomes (Staggered Event Study)



*Notes:* The above figures show event-study plots estimating the impact of state-level labor law amendments using the (Callaway & Sant'Anna, 2021) estimator. The outcome of interest is the (logged) welfare per employee (Panel a), the (logged) provident fund provision per employee (Panel b), the IHS transformation of profit per employee (Panel c), (logged) total output per employee (Panel d) and the log of the female to male wage ratio (Panel e). The unit of observation is the manufacturing establishment in a year. We keep establishments that report using some labor use in a given year. The solid line represents the average annual treatment effects, and the dashed lines denote the 95% confidence intervals. The treatment effects are with respect to the year before the amendment came into force (dashed vertical line). Specifications include establishment and year fixed effects. Standard errors are wild-bootstrapped and clustered by state.

*Source:* ASI 2009-2019.

Table 1: Firm Size and Relative Female Employment (ASI Data)

	(1)	(2)	(3)	(4)	(5)	(6)
	Female Proportion					
	Worker	Mandays	Worker	Mandays	Worker	Mandays
Panel A: Panel Estimates						
ln(Firm Size)	0.024*** (0.001)	0.023*** (0.001)	0.022*** (0.001)	0.022*** (0.001)	0.051*** (0.002)	0.049*** (0.002)
ln(Firm Size) <sup>2</sup>					-0.004*** (0.000)	-0.004*** (0.000)
Mean Female Proportion	.121	.119	.121	.12	.121	.12
R-Squared	.85	.856	.853	.859	.854	.86
Observations	784652	682058	784521	681939	784521	681939
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Indus. $\times$ Yr FE			Yes	Yes	Yes	Yes
State $\times$ Yr FE			Yes	Yes	Yes	Yes
Panel B: Cross-Sectional Estimates						
ln(Firm Size)	0.033*** (0.006)	0.032*** (0.006)	0.017*** (0.002)	0.016*** (0.002)	0.040*** (0.006)	0.038*** (0.005)
ln(Firm Size) <sup>2</sup>					-0.003*** (0.001)	-0.003*** (0.001)
Mean Female Proportion	.122	.121	.122	.121	.122	.121
R-Squared	.0565	.0539	.376	.378	.377	.379
Observations	836317	732074	836214	731979	836214	731979
Indus. $\times$ Yr FE			Yes	Yes	Yes	Yes
State $\times$ Yr FE			Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* The dependent variable is proportion of female workers in columns 1, 3 and 5 and proportion of of female worker mandays in columns 2, 4 and 6. Firm size is defined as log of number of male and female workers in the enterprise. Controls in Panel B are organisation type, sector (rural/urban) and year of initial production. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted by establishment level survey weights. Standard errors in parentheses are clustered at firm level for Panel A and at state-NIC (4-digit) level for Panel B. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Annual Survey of Industries 1998-2019.

Table 2: Firm Size and Relative Female Employment (Individual Data)

	All workers		Full time	
	(1)	(2)	(3)	(4)
6- 9	-0.004 (0.003)	-0.002 (0.004)	0.001 (0.004)	0.002 (0.004)
10-20	0.014** (0.004)	0.019*** (0.004)	0.017** (0.005)	0.023*** (0.005)
20 and above	0.032*** (0.005)	0.041*** (0.005)	0.042*** (0.006)	0.051*** (0.006)
Constant	0.182*** (0.002)	0.180*** (0.002)	0.165*** (0.002)	0.163*** (0.002)
Mean of DV	0.196	0.198	0.182	0.184
R-Squared	0.382	0.431	0.367	0.415
Observations	322795	316179	201485	197036
District x Yr FE	Yes	Yes	Yes	Yes
Indus. x Yr FE	Yes		Yes	
Occ x Yr FE	Yes		Yes	
Indus. x Occ x Yr FE		Yes		Yes
Controls	Yes	Yes	Yes	Yes

*Notes:* The dependent variable takes a value of one when a worker is female and zero otherwise. Controls include age, age square, education level, religion, social group, income decile and marital status. Mean of DV denotes the mean of the dependent variable. The sample includes all individuals working in the non-cultivation sector who work as paid employees. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted by individual survey weights. Standard errors in parentheses are clustered at district level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* NSS rounds 55, 61, 66 and 68, PLFS 2017-18 and PLFS 2018-19. Columns 3-4 only contain data from NSS rounds 55, 61, 66 and 68 whereas columns 1 and 2 additionally contain data from PLFS 2017-18 and PLFS 2018-19. This is because PLFS does not contain details on part/full time work.

Table 3: Effect of Amendments on Relative Female Employment and Firm Size (DID Estimates)

	(1)	(2)	(3)	(4)
	Female proportion		ln(Firm size)	
			Employees	Output
Amendment	0.006*	0.004*	0.054**	0.192**
	(0.003)	(0.002)	(0.025)	(0.091)
	[0.13]	[0.15]	[0.11]	[0.09]
Mean of Female Proportion	.106	.106		
R-Squared	.857	.858	.895	.747
Observations	462298	462298	462298	462298
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Indus. $\times$ Yr FE	No	Yes	Yes	Yes

*Notes:* The table reports difference-in-differences estimation results for the outcome variables of relative female employment and firm size using two-way fixed effects. The dependent variable is proportion of female workers in columns 1-2, log total employees in column 3 and log total value of output in column 4. Treated states are Rajasthan, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are clustered at the state level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively. P-values from wild-bootstrap clustering method are provided in square brackets.

*Source:* Annual Survey of Industries 2009-2019.

Table 4: Amenities and Relative Female Employment (Individual data)

	(1)	(2)	(3)	(4)
Part Time	0.187*** (0.013)	0.171*** (0.013)		
Written	0.022*** (0.007)	0.027*** (0.007)	0.017*** (0.005)	0.020*** (0.005)
Healthcare/ Maternity	0.019*** (0.006)	0.020*** (0.006)	0.018*** (0.005)	0.019*** (0.005)
Pension/PF/Gratuity	-0.052*** (0.008)	-0.059*** (0.008)	-0.050*** (0.007)	-0.053*** (0.008)
Paid Leave	-0.009* (0.005)	-0.004 (0.005)	-0.011** (0.004)	-0.006 (0.004)
Constant	0.195*** (0.002)	0.195*** (0.002)	0.205*** (0.002)	0.204*** (0.002)
Mean of DV	0.197	0.198	0.199	0.201
R-Squared	0.388	0.436	0.386	0.436
Observations	157238	154291	263028	257999
District x Yr FE	Yes	Yes	Yes	Yes
Ind x Yr FE	Yes		Yes	
Occ x Yr FE	Yes		Yes	
Ind x Occ x Yr FE		Yes		Yes
Controls	Yes	Yes	Yes	Yes

*Notes:* The dependent variable takes a value of one when a worker is female and zero otherwise. Controls include age, age square, education level, religion, social group, income decile, sector(rural/urban) and marital status. Mean of DV denotes the mean of the dependent variable. The sample includes all individuals working in the non-cultivation sector as paid employees. Regressions are weighted by individual survey weights. Standard errors in parentheses are clustered at district level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* NSS rounds 61, 66 and 68 in columns 1-2. Columns 3 and 4 additionally include PLFS 2017-18 and PLFS 2018-19 because the PLFS do not contain capture part/full time work. NSS 55 only contains information on part/full time work and pension and hence is dropped from this analyses.

Table 5: Firm Size and Amenities (Individual Data)

<i>Dependent Variable:</i>	Part -time	Written Contract	Healthcare /Maternity	Pension	Paid Leave
	(1)	(2)	(3)	(4)	(5)
6- 9	-0.003 (0.003)	0.021*** (0.004)	0.016*** (0.003)	0.028*** (0.003)	0.030*** (0.003)
10-20	0.001 (0.003)	0.049*** (0.004)	0.047*** (0.004)	0.078*** (0.005)	0.069*** (0.005)
20 and above	-0.001 (0.004)	0.140*** (0.007)	0.151*** (0.008)	0.221*** (0.008)	0.161*** (0.007)
Constant	0.038*** (0.002)	0.153*** (0.002)	0.120*** (0.003)	0.178*** (0.003)	0.228*** (0.003)
Mean of DV	0.036	0.266	0.222	0.326	0.359
R-Squared	0.154	0.509	0.493	0.632	0.593
Observations	204414	266603	258175	299870	266526
District x Yr FE	Yes	Yes	Yes	Yes	Yes
Ind x Occ x Yr FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

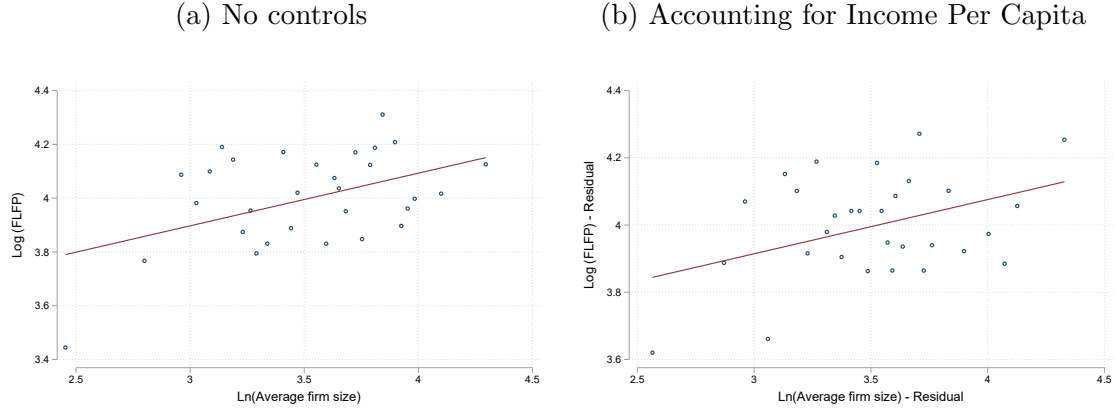
*Notes:* In column 1 the dependent variable takes a value of one when a worker is working part time and zero otherwise. In column 2 the dependent variable takes a value of one when a worker has a written contract and zero otherwise. In column 3-5 the dependent variable takes a value of one if the mentioned benefit is available to the worker and zero otherwise. Controls include age, age square, education level, religion, social group, income decile, sector(rural/urban) and marital status. Mean of DV denotes the mean of the dependent variable. The sample includes all individuals working in the non-cultivation sector who work as paid employees. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted by individual survey weights. Standard errors in parentheses are clustered at district level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Column 1 contain data from NSS rounds 55, 61, 66 and 68. Column 4 contains data from NSS rounds 55, 61, 66 and 68, PLFS 2017-18 and PLFS 2018-19. Columns 2, 3 and 5 contain data from NSS rounds 61, 66 and 68 and PLFS 2017-18 and PLFS 2018-19. This is because NSS round 55 only has data on whether the respondent was covered under any type of provident fund or had part/full time work. PLFS does not contain details on part/full time work.

# ONLINE APPENDIX

## A Appendix: Figures and Tables

Figure A.1: Female Labor Force participation and Firm Size: Cross-country Evidence

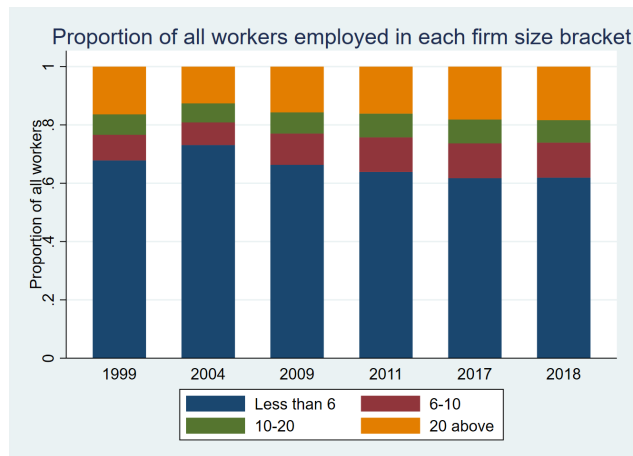


*Notes:* Panel (a) plots the binscatter of log of female labor force participation (FLFP) vs. the log of average firm size in the formal sector across countries. Panel (b) plots the binscatter of log of FLFP vs. the log of average firm size in the formal sector across countries, after controlling for the association between FLFP and firm size with the log of Gross National Income (GNI) per capita in PPP terms. Panel (a), slope=0.19 (p-value=0.007) and Panel (b), slope=0.16 (p-value=0.038)

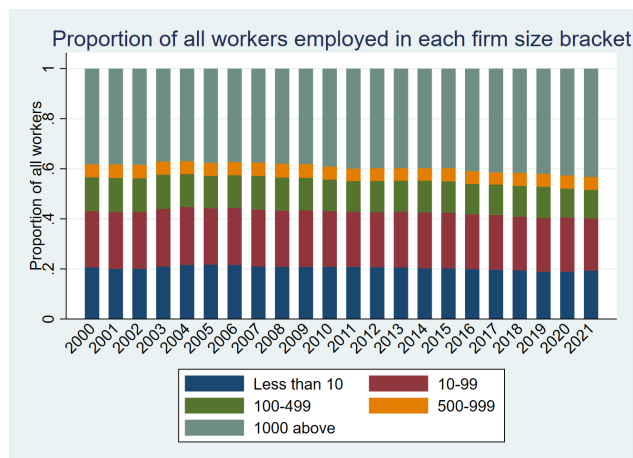
*Source:* [OECD](#) report for firm size data for the OECD countries for year 2014 or the latest year of availability. This is based on enterprise data collected by individual countries. For other countries we use the World Bank Enterprise Data (WBED) for firm size (average between 2006-2019). WBED is collected only for enterprises in the formal sector and hence we restrict the firms to size more than 10 for the OECD countries when calculating the average firm size. This is to maintain comparability across the two sources. FLFP rates for ages 15-64 are obtained from Our World in Data (average between 2006-2019). Total countries are 156 after omitting countries which are outliers in average firm size (3 countries had average firm size more than 100).

Figure A.2: Distribution of Workers by Firm Size Categories: India vs US

(a) India



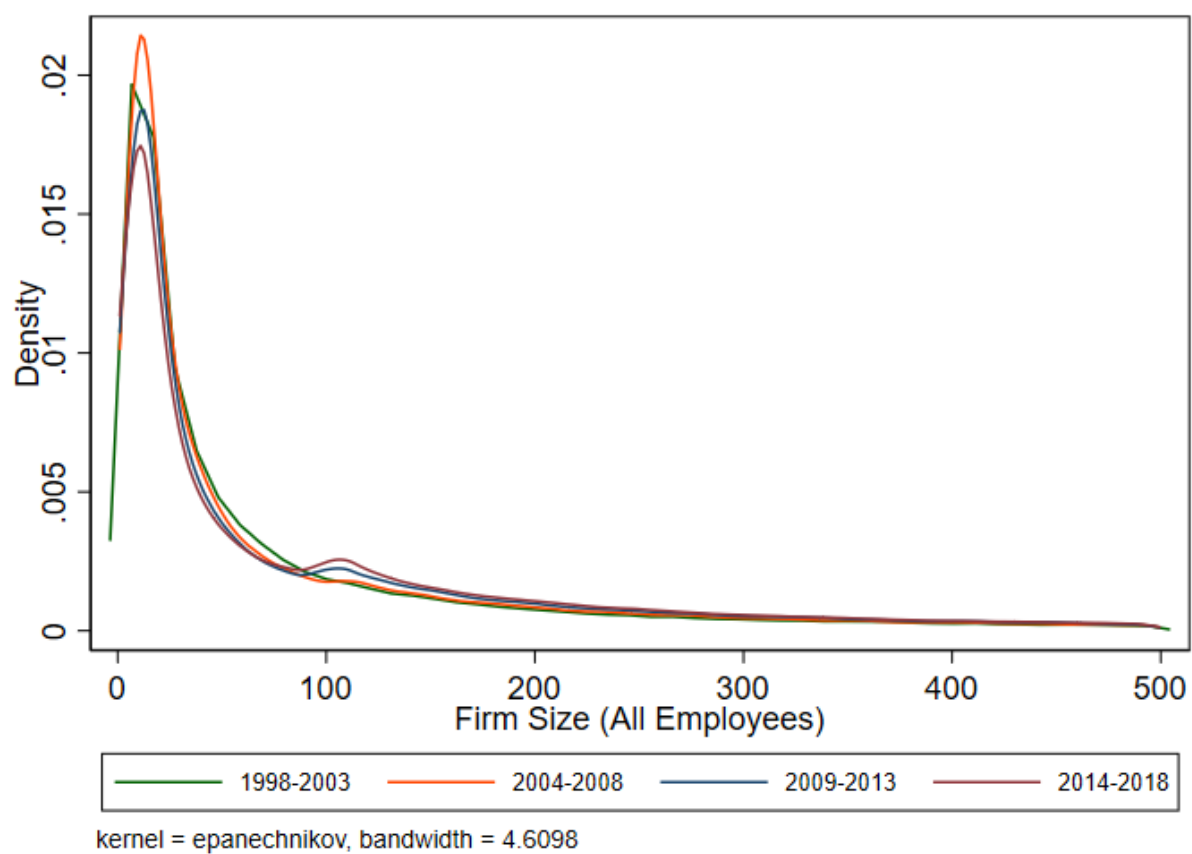
(b) USA



*Notes:* Panels (a) and (b) plot proportion of workers in each firm size category for India and the US, respectively.

*Source:* NSS and PLFS (India) and CPS (US), various rounds.

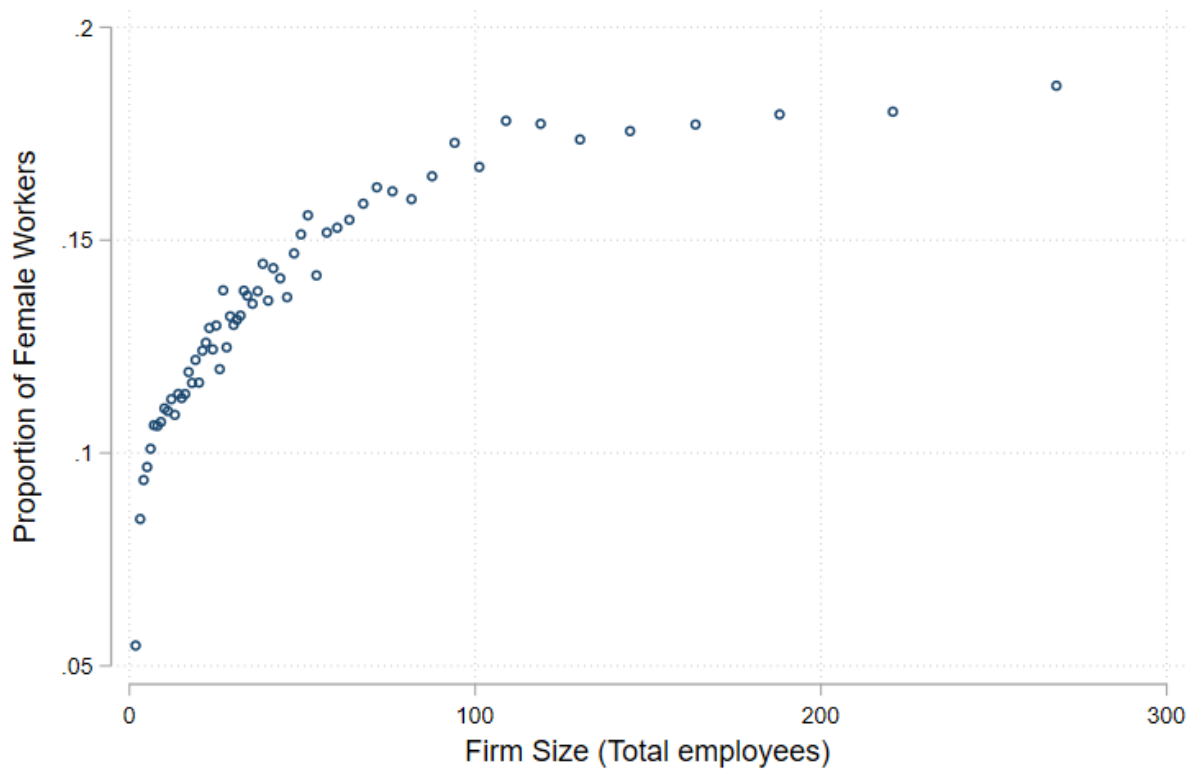
Figure A.3: Firm size distribution over years (ASI data)



*Notes:* We plot the density of firm size distribution for total employees (workers+supervisors+other+contract workers).

*Source:* Annual Survey of Industries 1998-2019.

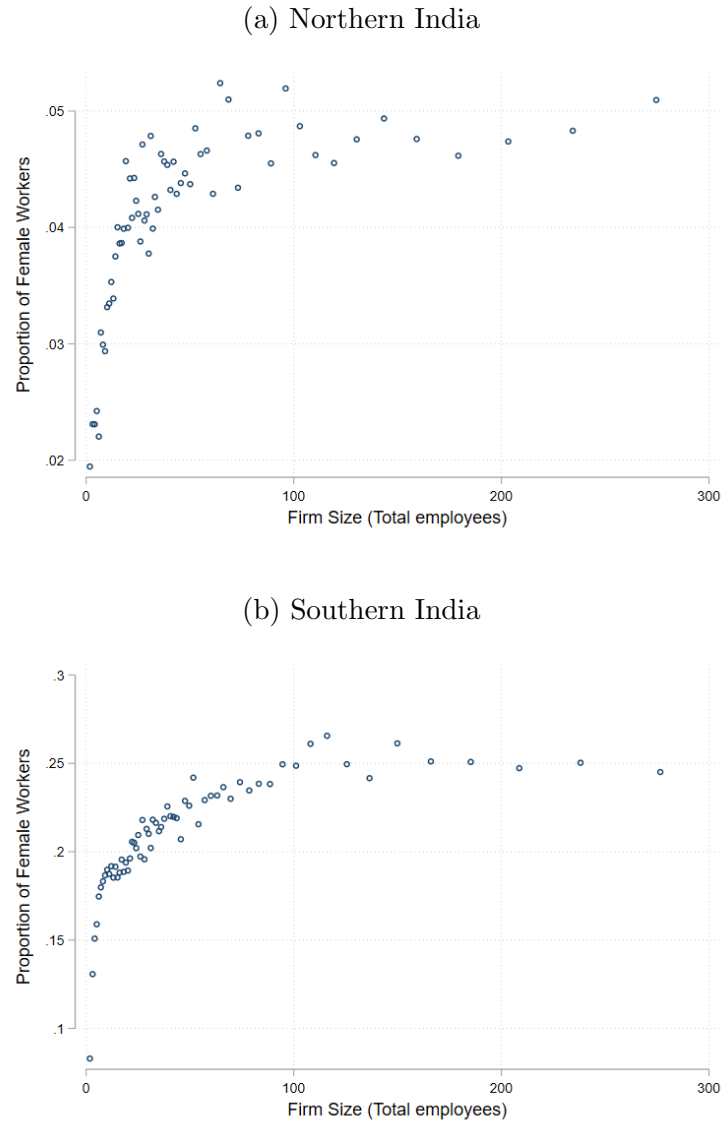
Figure A.4: Proportion of Female Workers across Firm Size (ASI data): Excluding Public Enterprises



*Notes:* The figure plots the binscatter between the proportion of female workers and total workers in a firm after excluding public sector enterprises enterprises.

*Source:* Annual Survey of Industries 1998-2019.

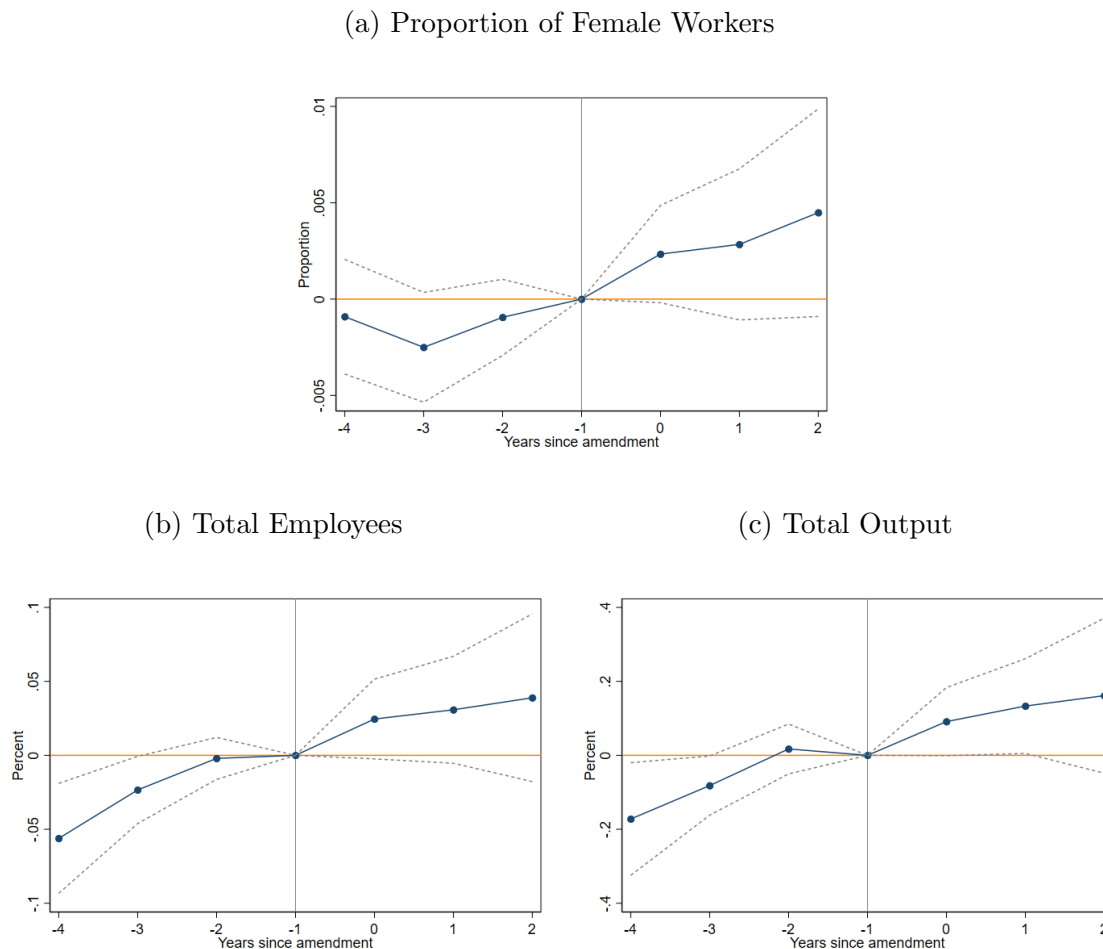
Figure A.5: Proportion of Female Workers across Firm Size (ASI data): North vs South



*Notes:* Panels (a) and (b) plots the binscatter between the proportion of female workers and total workers in a firm for the northern and southern states of India, respectively.

*Source:* Annual Survey of Industries 1998-2019.

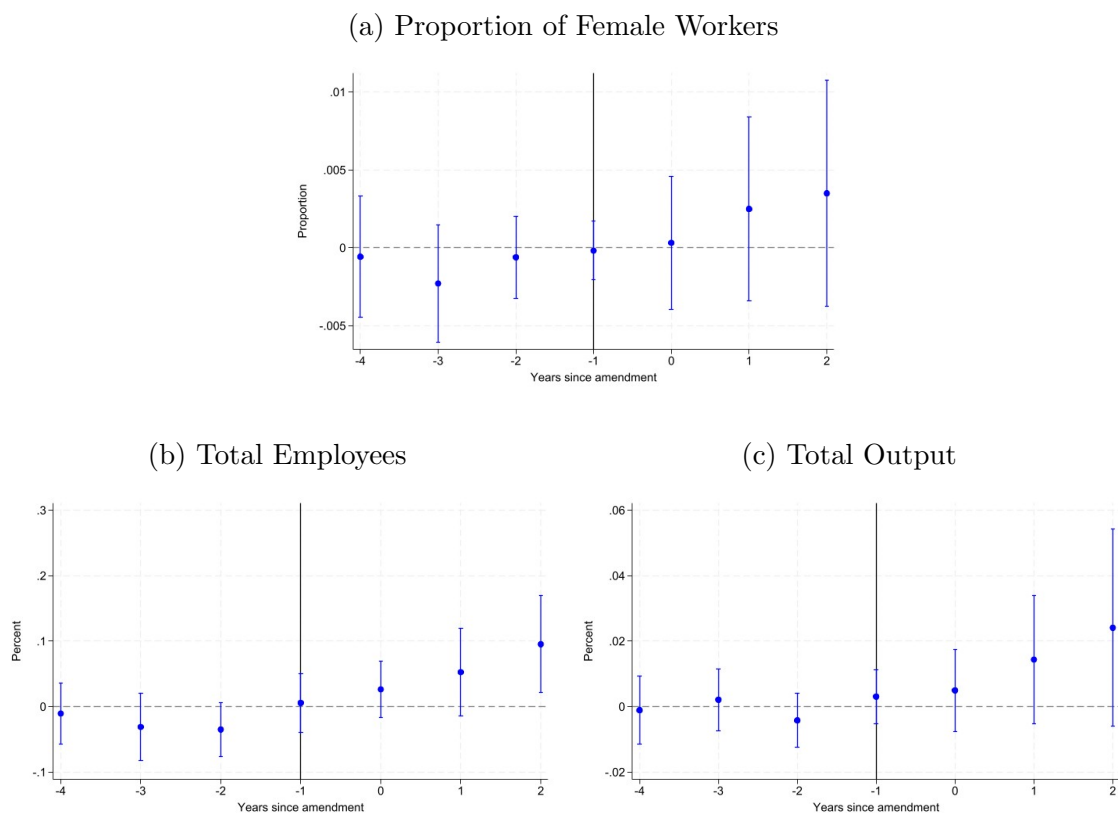
Figure A.6: Impact of Amendments on Female Employment and Firm Size (TWFE Event Study)



*Notes:* The above figures show event-study plots estimating the impact of state-level labor law amendments on the proportion of female workers and firm-size measures using the two-way fixed effects estimator. The outcome of interest is the proportion of female workers (Panel a), (logged) number of total employees (Panel b), and (logged) total value of output (Panel c). The unit of observation is the manufacturing establishment in a year. We keep establishments that report using some labor in a given year. The solid line represents the average annual treatment effects, and the dashed lines denote the 95% confidence intervals. The treatment effects are with respect to the year before the amendment came into force (dashed vertical line). Specifications include establishment fixed effects, year fixed effects and industry-year fixed effects. Standard errors are clustered by state.

*Source:* Annual Survey of Industries 2009-2019.

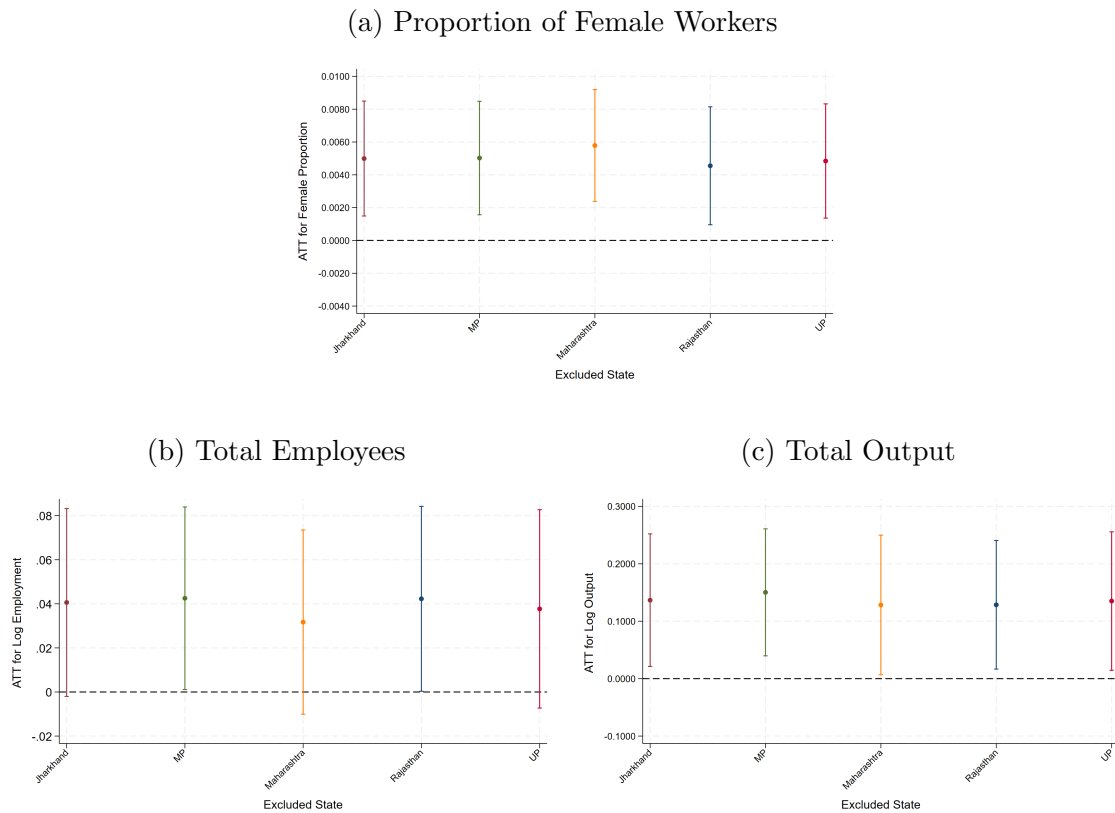
Figure A.7: Impact of Amendments on Relative Female Employment and Firm Size (Synthetic DiD Event Study)



*Notes:* The above figures show event-study plots estimating the impact of state-level labor law amendments using the estimator Synthetic Difference-in-Differences (SDID) estimator developed by [Arkhangelsky et al. \(2021\)](#) and extended to an event-study framework by [Clarke, Pailanir, Athey, and Imbens \(2024\)](#) and [Ciccia \(2024\)](#). The outcome of interest is the proportion of female workers (Panel a), (logged) number of total employees (Panel b), and (logged) total value of output (Panel c). The unit of observation is the state-year, obtained by computing average value of the outcome variable across all establishments that report using some labor in a given state-year. Unlike traditional event study estimators, the SDID event-study framework does not rely on a designated base period. Instead, it estimates absolute effects—measuring the difference between treated and synthetic control groups at each event time. 95% confidence intervals for each estimate are plotted. Standard errors are bootstrapped at state level. The vertical line marks the year before the treatment occurs.

*Source:* ASI 2009-2019.

Figure A.8: Impact of Amendments on Relative Female Employment and Firm Size: Robustness (Dropping States)



*Notes:* The above figures show the average treatment effect on the treated of the labor law amendments using [Callaway and Sant'Anna \(2021\)](#) estimator. The outcome of interest is the proportion of female workers (Panel a), (logged) number of total employees (Panel b) and (logged) total value of output (Panel c). The unit of observation is the manufacturing establishment in a year. We keep establishments that report using some labor in a given year. The solid line represents the average annual treatment effects, and the dashed lines denote the 90% confidence intervals. The treatment effects are with respect to the year before the amendment came into force (dashed vertical line). Specifications include establishment and year fixed effects. Standard errors are wild-bootstrapped and clustered by state.

*Source:* Annual Survey of Industries 2009-2019.

Table A.1: Descriptive statistics

	(1)	(2)	(3)
	Mean	SD	N
<b>Panel A: Female Employment</b>			
Proportion of Female Workers	0.122	0.241	870153
Proportion of Female Mandays	0.120	0.239	761843
<b>Panel B: Firm Size</b>			
Firm Size (All Employees)	75.915	414.969	964485
Firm Size (Output, INR)	2.734e+08	5.523e+09	964485
<b>Panel C: Other Firm Variables</b>			
Welfare per employee (INR)	2280.457	4488.016	954120
PF per employee (INR)	3501.183	5406.843	954118
Profit per employee (INR)	90594.628	163397.053	901006
Labor Productivity (INR, output per employee)	1435557.829	1865492.456	954121
Gender Wage Ratio (female/male)	0.860	0.236	230141

*Notes:* Proportion of female workers is calculated as female workers out of total workers. Proportion of female mandays is defined as total female worker mandays out of total worker mandays. Firm Size (All Employees) refers to all employees including manufacturing workers, supervisors, other employees and contract workers. Firm size (Output) is defined as total value of output (price  $\times$  quantity) produced by a firm deflated by two digit industry specific Wholesale Price Index (WPI) with 2004 as the base year. Welfare expenses refer to group benefits like direct expenditure on maternity, creches, canteen facilities, educational, cultural and recreational facilities, paid per employee annually. Provident Fund (PF) is annual social security contribution of the employer paid per employee. Both the expenditures are deflated using the CPI with base year as 2004. Profits are deflated by two digit industry specific Wholesale Price Index (WPI) with 2004 as the base year and divided by total employees. Labor productivity is defined as total value of real output per employee. Gender wage gap is defined as the ratio of female wage rate by male wage rate.

*Source:* Annual Survey of Industries (ASI) 1998-2019.

Table A.2: Firm Size and Relative Female Employment (ASI data): Robustness to Alternative Definitions and Controls

	(1)	(2)	(3)	(4)
	Female Proportion			
	Worker	Mandays	Worker	Mandays
ln(Firm Size (Output))	0.004*** (0.000)	0.005*** (0.000)		
ln(Firm Size)			0.022*** (0.001)	0.022*** (0.001)
Export Share			0.003 (0.002)	0.004* (0.002)
Mean Female Proportion	.121	.119	.12	.12
R-Squared	.852	.858	.875	.876
Observations	784521	682036	461775	461616
Firm FE	Yes	Yes	Yes	Yes
Indus. $\times$ Yr FE	Yes	Yes	Yes	Yes
State $\times$ Yr FE	Yes	Yes	Yes	Yes

*Notes:* The dependent variable is proportion of female workers in columns 1 and 3, and proportion of female worker mandays in columns 2 and 4. Firm size is defined as log of number of total employees in the enterprise in columns 3-4. In columns 1-2, firm size (Output) is defined as log of total real value of output. Export share capture the proportion of value of output that is exported by a firm in a given year. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted by establishment level survey weights. Standard errors in parentheses are clustered at firm level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Annual Survey of Industries 1998-2019.

Table A.3: Firm Size Categories and Relative Female Employment (ASI Data: Panel Estimates)

	(1)	(2)	(3)	(4)
	Worker	Mandays	Worker	Mandays
5-10	0.039*** (0.002)	0.037*** (0.002)	0.039*** (0.002)	0.038*** (0.002)
10-25	0.059*** (0.002)	0.057*** (0.002)	0.059*** (0.002)	0.058*** (0.002)
25-50	0.075*** (0.003)	0.072*** (0.003)	0.073*** (0.002)	0.072*** (0.003)
50-100	0.085*** (0.003)	0.082*** (0.003)	0.082*** (0.003)	0.080*** (0.003)
100-300	0.094*** (0.003)	0.090*** (0.003)	0.090*** (0.003)	0.087*** (0.003)
>= 300	0.104*** (0.003)	0.100*** (0.003)	0.097*** (0.003)	0.094*** (0.003)
Mean Female Proportion	.121	.119	.121	.119
R-Squared	.8495031	.8558765	.8534086	.8592827
Observations	784652	682155	784521	682036
Firm FE	Yes	Yes	Yes	Yes
Indus. $\times$ Yr FE	No	No	Yes	Yes
State $\times$ Yr FE	No	No	Yes	Yes

*Notes:* The dependent variable is proportion of female workers in columns (1) and (3) and proportion of female worker mandays in columns (2) and (4). In the rows, firm size is a categorical variable that classifies firms into groups based on their number of total employees. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted by establishment level survey weights. Standard errors in parentheses are clustered at firm level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Annual Survey of Industries 1998-2019.

Table A.4: Firm Size and Relative Female Employment (Census Data)

Dependent variable:	Total				Hired	
	(1)	(2)	(3)	(4)	(5)	(6)
log (Firm Size)	0.070*** (0.002)	0.055*** (0.002)	0.092*** (0.002)	0.158*** (0.004)		
log (Firm Size) <sup>2</sup>				-0.035*** (0.001)		
log (Firm Size (Hired))					0.028*** (0.001)	0.025*** (0.002)
log (Firm Size (Hired)) <sup>2</sup>						0.001 (0.001)
Mean Female Proportion	.187	.187	.182	.182	.153	.153
R-Squared	.132	.278	.638	.644	.303	.303
Observations	1.31e+08	1.31e+08	1.17e+08	1.17e+08	3.02e+07	3.02e+07
District $\times$ Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Yr FE	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes

*Notes:* The dependent variable is defined as the proportion of female employees among total employees (including unpaid employees which are generally family members) in columns 1-4. The dependent variable is defined as the proportion of hired female employees among all hired employees in columns 5-6.. Firm size is defined as total hired and unpaid workers in columns 1-4. Firm size is defined as hired workers in columns 5-6. Controls used are enterprises operation type, ownership by gender (male or female owner), source of finance, ownership type and sector of operation (rural/urban). District by year and Industry by year fixed effects are included in all specifications. Standard errors in parentheses are clustered at district level within each year. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Notes:* Economic Census rounds 1999, 2005 and 2013.

Table A.5: Firm Size Categories and Relative Female Employment across Economic Sectors (Census Data)

	(1)	(2)	(3)	(4)
	Agriculture	Manufacturing	Construction	Services
Firm Size (Hired)				
5-10	0.017*** (0.007)	0.030*** (0.003)	0.072*** (0.004)	0.051*** (0.002)
10-25	0.082*** (0.008)	0.071*** (0.004)	0.108*** (0.005)	0.091*** (0.004)
25-50	0.094*** (0.012)	0.093*** (0.007)	0.118*** (0.011)	0.105*** (0.005)
50-100	0.080*** (0.016)	0.111*** (0.011)	0.126*** (0.029)	0.106*** (0.010)
100-300	0.048 (0.034)	0.091*** (0.008)	0.231** (0.107)	0.100*** (0.014)
>= 300	0.390*** (0.041)	0.094*** (0.013)	0.163*** (0.047)	0.225*** (0.036)
Mean Female Proportion	.304	.199	.11	.125
R-Squared	.191	.407	.19	.246
Observations	1185697	8600762	458530	1.99e+07
District by Yr FE	Yes	Yes	Yes	Yes
Industry by Yr FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

*Notes:* The dependent variable is defined as the proportion of female hired employees among all hired employees. Firm size is defined as categories of hired employees. Controls used are enterprises operation type, ownership by gender (male or female owner), source of finance, ownership type and sector of operation (rural/urban). Columns (1), (2), (3) and (4) shows the estimates for agricultural, manufacturing, construction and services based enterprises, respectively. An agricultural enterprise is defined as one engaged in livestock production and agricultural services including hunting, forestry, logging and fishing. District by year and Industry by year fixed effects are included in all specifications. Standard errors in parentheses are clustered at district level within each year. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Economic Census rounds 1999, 2005 and 2013.

Table A.6: Firm Size Categories and Relative Female Employment across Economic Sectors (Census Data): By Rural/Urban

	(1)	(2)	(3)	(4)
	Agriculture	Manufacturing	Construction	Services
Panel A: Rural Sector				
Firm Size (Hired)				
5-10	0.016** (0.008)	0.038*** (0.005)	0.081*** (0.004)	0.043*** (0.003)
10-25	0.083*** (0.010)	0.082*** (0.006)	0.114*** (0.006)	0.074*** (0.005)
25-50	0.088*** (0.013)	0.128*** (0.011)	0.130*** (0.011)	0.096*** (0.010)
50-100	0.070*** (0.018)	0.149*** (0.018)	0.100*** (0.015)	0.103*** (0.022)
100-300	0.059* (0.033)	0.107*** (0.012)	0.067*** (0.020)	0.092*** (0.016)
>= 300	0.405*** (0.042)	0.098*** (0.018)	0.130** (0.058)	0.235*** (0.035)
Mean Female Proportion	.321	.273	.115	.159
R-Squared	.187	.408	.226	.266
Observations	1039284	4106806	215245	6333407
Panel B: Urban Sector				
Firm Size (Hired)				
5-10	0.019** (0.008)	0.027*** (0.003)	0.066*** (0.004)	0.051*** (0.002)
10-25	0.048* (0.027)	0.064*** (0.004)	0.103*** (0.008)	0.091*** (0.004)
25-50	0.139*** (0.020)	0.070*** (0.006)	0.107*** (0.017)	0.099*** (0.006)
50-100	0.166*** (0.029)	0.077*** (0.008)	0.142*** (0.045)	0.098*** (0.009)
100-300	-0.085 (0.103)	0.080*** (0.009)	0.343*** (0.129)	0.098*** (0.018)
>= 300	0.233*** (0.062)	0.091*** (0.017)	0.200*** (0.064)	0.218*** (0.046)
Mean Female Proportion	.184	.132	.106	.109
R-Squared	.211	.37	.184	.238
Observations	146355	4493915	243179	1.36e+07
District by Yr FE	Yes	Yes	Yes	Yes
Industry by Yr FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

*Notes:* The dependent variable is defined as the proportion of female hired employees among all hired employees. Firm size is defined as categories of hired employees. Controls used are enterprise operation type, ownership by gender (male or female owner), source of finance and ownership type. Columns (1), (2), (3) and (4) shows the estimates for agricultural, manufacturing, construction and services based enterprises, respectively. An agricultural enterprise is defined as one engaged in livestock production and agricultural services including hunting, forestry, logging and fishing. Panel (A) and Panel (B) restrict the enterprises to rural and urban India, respectively. District by year and Industry by year fixed effects are included in all specifications. Standard errors in parentheses are clustered at district level within each year. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Economic Census rounds 1999, 2005 and 2013.

Table A.7: Firm Size Categories and Relative Female Employment across Economic Sectors (Census Data): By Owner Gender

	(1)	(2)	(3)	(4)
	Agriculture	Manufacturing	Construction	Services
Panel A: Male Owned Firms				
Firm Size (Hired)				
5-10	0.022*** (0.007)	0.040*** (0.003)	0.077*** (0.003)	0.062*** (0.002)
10-25	0.089*** (0.009)	0.081*** (0.005)	0.112*** (0.005)	0.106*** (0.004)
25-50	0.103*** (0.012)	0.103*** (0.008)	0.125*** (0.011)	0.125*** (0.005)
50-100	0.080*** (0.017)	0.124*** (0.012)	0.133*** (0.029)	0.123*** (0.011)
100-300	0.039 (0.031)	0.102*** (0.009)	0.252** (0.107)	0.115*** (0.015)
>= 300	0.407*** (0.045)	0.112*** (0.013)	0.209*** (0.058)	0.243*** (0.037)
Mean Female Proportion	.272	.132	.0968	.096
R-Squared	.187	.193	.146	.137
Observations	1019916	7612365	441321	1.87e+07
Panel B: Female Owned Firms				
Firm Size (Hired)				
5-10	-0.055*** (0.015)	-0.145*** (0.012)	-0.060*** (0.016)	-0.117*** (0.007)
10-25	-0.002 (0.036)	-0.094*** (0.013)	-0.036 (0.027)	-0.078*** (0.008)
25-50	-0.044 (0.029)	-0.088*** (0.013)	-0.066** (0.028)	-0.097*** (0.009)
50-100	0.092** (0.044)	-0.088*** (0.020)	-0.023 (0.067)	-0.089*** (0.013)
100-300	0.099 (0.113)	-0.083*** (0.018)	-0.016 (0.060)	-0.073*** (0.016)
>= 300	0.295*** (0.052)	-0.084*** (0.029)	-0.104 (0.069)	0.063 (0.057)
Mean Female Proportion	.5	.72	.446	.562
R-Squared	.143	.419	.482	.319
Observations	165645	988264	16983	1238976
District by Yr FE	Yes	Yes	Yes	Yes
Industry by Yr FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

*Notes:* The dependent variable is defined as the proportion of female hired employees among all hired employees. Firm size is defined as hired employees. Controls used are enterprise operation type, ownership by gender (male or female owner), source of finance, ownership type and sector of operation (rural/urban). Columns (1), (2), (3) and (4) shows the estimates for agricultural, manufacturing, construction and services based enterprises, respectively. An agricultural enterprise is defined as one engaged in livestock production and agricultural services including hunting, forestry, logging and fishing. Panel (A) shows the results for male owned enterprises while panel (B) for female owned enterprises. District by year and Industry by year fixed effects are included in all specifications. Standard errors in parentheses are clustered at district level within each year. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Economic Census rounds 1999, 2005 and 2013.

Table A.8: Descriptive Statistics - Individual Data

	(1)	(2)	(3)
	N	Mean	SD
<b>Panel A: Outcome Variables</b>			
Proportion of Female Workers	322911	0.192	0.394
Wage Rate (INR, Daily)	300386	440.741	531.213
Proportion of Part Time Workers	209000	0.037	0.189
Proportion of Workers with Written Contract Holders	271725	0.204	0.403
Proportion of Workers with Healthcare/ Maternity Benefits	263240	0.174	0.379
Proportion of Workers with Pension benefits	306504	0.258	0.438
Proportion of Workers with Paid Leave	271644	0.290	0.454
<b>Panel B: Firm Size Variable</b>			
Less than 6 Workers	322911	0.440	0.496
6-10 Workers	322911	0.165	0.371
10-20 Workers	322911	0.116	0.321
More than 20 workers	322911	0.279	0.448

*Notes:* Proportion of female workers is calculated as the number of female workers divided by all workers. Wage rate is calculated by dividing total earnings by total days worked in the last reference week. It is deflated using the consumer price index and is constant at 2017 prices. We calculate the proportion of workers availing any benefit - part time, written contract, healthcare/maternity, pension and paid leave. NSS rounds 55 does not contain details on paid leave, written contract, healthcare/ maternity; It only has data on whether the respondent was covered under any type of provident fund (pension). PLFS does not contain details on part/full time work. This leads to variation in observations for the proportion of workers who avail benefits. Panel B shows the proportion of workers in each firm size category captured in the survey. The sample includes all individuals working in the non-cultivation sector who work as paid employees.

*Source:* NSS rounds 55, 61, 66 and 68, PLFS 2017-18 and PLFS 2018-19. For benefits received in a job, rounds where a given benefit is captured is used.

Table A.9: Firm Size and Female Employment (U.S. data)

	All worker types		Full time	
	(1)	(2)	(3)	(4)
10-99	0.000 (0.001)	0.002 (0.001)	0.011*** (0.002)	0.012*** (0.001)
100-499	0.006*** (0.002)	0.009*** (0.002)	0.022*** (0.002)	0.024*** (0.002)
500-999	0.013*** (0.002)	0.014*** (0.002)	0.028*** (0.002)	0.029*** (0.002)
1000+	0.010*** (0.002)	0.012*** (0.001)	0.028*** (0.002)	0.029*** (0.002)
Constant	0.479*** (0.001)	0.480*** (0.001)	0.426*** (0.001)	0.426*** (0.001)
Mean of DV	0.495	0.497	0.451	0.453
R-Squared	0.356	0.409	0.358	0.415
Observations	1864465	1836031	1506122	1478588
County x Yr FE	Yes	Yes	Yes	Yes
Ind x Yr FE	Yes		Yes	
Occ x Yr FE	Yes		Yes	
Ind x Occ x Yr FE		Yes		Yes
Controls	Yes	Yes	Yes	Yes

*Notes:* The dependent variable takes a value of one when a worker is female and zero otherwise. Controls include age, age square, education level, race, income decile and marital status. Mean of DV denotes the mean of the dependent variable. Data includes all salaried individuals working in the private or government sector. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted by individual survey weights. Standard errors in parentheses are clustered at county-year level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* ASEC Supplement, Current Population Survey (USA), 2000-2021

Table A.10: Summary Statistics: Treatment vs Control States

	(1)	(2)	(3)	(4)	(5)	(6)
	Treated = 0			Treated = 1		
	Mean	SD	N	Mean	SD	N
Proportion of Female Workers	0.13	0.25	157146	0.04	0.14	63545
Firm Size (Employees)	78.23	430.27	157146	78.24	323.70	63545
Firm Size (Output)	1.03e+08	2.42e+08	157146	1.29e+08	2.73e+08	63545

*Notes:* Proportion of female workers are defined as total female workers in permanent employment out of total workers in permanent employment. Firm Size (Employees) refers to all employees including manufacturing workers, contract workers, supervisors and unpaid employees. Firm size (Output) is defined as total value of output (price  $\times$  quantity) produced by a firm deflated by two digit industry specific Wholesale Price Index (WPI) with 2004 as the base year.

*Source:* Annual Survey of Industries 2009–2019.

Table A.11: Effect of Amendments on Relative Female Employment and Firm Size (Staggered DID Estimates): Robustness to alternative definitions

	Any female (1)	ln(Female workers) (2)	ln(Male workers) (3)	Female proportion (4)
	Workers	Workers	Workers	Mandays
Amendment	0.013* (0.007)	0.062# (0.04)	.0086 (0.025)	0.005** (0.002)
Mean	.287	23.4	86.7	.108
Observations	390,288	390,288	390,288	390,288

*Notes:* The table reports difference-in-differences estimation results for the outcome variables of firm size and female employment estimated using the method proposed by [Callaway and Sant'Anna \(2021\)](#). The dependent variable is an indicator variable that takes a value of one if a female worker is hired and zero otherwise in column 1, log number of female workers in column 2, log number of male workers in column 3, proportion of female worker mandays in column 4. Treated states are Rajasthan, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are wild-bootstrapped and clustered at the state level. \*\*\*, \*\*, \*, # show significance at 1%, 5%, 10% and 15% respectively.

*Source:* Annual Survey of Industries 2009-2019.

Table A.12: Effect of Amendments on Relative Female Employment and Firm Size (Staggered DID Estimates): Other Robustness

	(1)	(2)	(3)
	Female Proportion	ln(Firm Size)	
	Workers	Employees	Output
Panel A: Extended time			
Amendment	.005** (0.002)	0.04# (0.026)	0.136* (0.069)
Mean of Female Proportion	.107		
Observations	618,107	618,107	618,107
Panel B: Dropping Night-Shift Amending States			
Amendment	0.006*** (0.002)	0.03 (0.02)	0.160** (0.077)
Mean of Female Proportion	0.13		
Observations	281,405	281,405	281,405

*Notes:* The table reports difference-in-differences estimation results using the method proposed by [Callaway and Sant'Anna \(2021\)](#). The dependent variable is proportion of female workers in column 1, log total employees in column 2, and log total value of output in column 3. Treated states are Rajasthan, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively in Panel (a). Madhya Pradesh, Maharashtra, Uttar Pradesh are dropped from Panel B. All years included from 2001 in Panel A. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are wild-bootstrap clustered at the state level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Annual Survey of Industries 2009-2019 in Panel C and 2001-2019 in Panel A.

Table A.13: Effect of Amendments on Number of Firms (DID Estimates)

	(1)	(2)	(3)	(4)
	number of firms		ln(number of firms)	
Amendment	0.031 (1.599)	0.005 (1.829)	0.051 (0.046)	0.048 (0.055)
Mean of number of firms	28.6	28.7	28.6	28.7
R-Squared	.127	.425	.191	.722
Observations	18778	18710	18778	18710
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Indus. $\times$ Yr FE	No	Yes	No	Yes

*Notes:* The table reports difference-in-differences estimation results for the outcome variables of number of firms in a given state, industry (nic 3 digit) and year. The dependent variable is number of firms in columns (1)-(2) and log number of firms in columns (3)-(4). Treated states are Rajasthan, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors clustered at the state level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Annual Survey of Industries 2009-2019.

Table A.14: Effect of Amendments on Other Firm Outcomes (DID Estimates): Alternative Mechanisms

	(1)	(2)	(3)	(4)
	Share Exports	Exports Indicator	Contract Workers	Permanent Employees
Amendment	-0.003 (0.003)	-0.009 (0.007)	0.021 (0.034)	0.051** (0.023)
Mean	.0375	.0703	29.3	73.6
R-Squared	.605	.507	.788	.887
Observations	462298	462298	462298	462298
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Indus. $\times$ Yr FE	Yes	Yes	Yes	Yes

*Notes:* The table reports difference-in-differences estimation results for the outcome variables of share of exports in a firm's output (column 1), whether a firm exports (column 2), the log of contract workers hired by a firm (column 3) and the log of permanent employees (all employees excluding contract workers). Treated states are Rajasthan, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors clustered at the state level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Annual Survey of Industries 2009-2019.

Table A.15: Impact of Amendments on Relative Female Employment and Firm Size: By Pre-Treatment Firm Size

	(1)	(2)	(3)
	Female Proportion	Employment	Output
Panel A : Firm Size [ $< 100$ ]			
Amendment	0.004** (0.002)	0.052* (0.027)	0.178** (0.084)
Mean of Proportion	0.098		
Observations	181000	181000	181000
Panel B : Firm Size [ $100 - 300$ ]			
Amendment	0.006* (0.003)	0.067* (0.039)	0.191** (0.074)
Mean of Proportion	0.124		
Observations	84201	84201	84201
Panel C : Firm Size [ $\geq 300$ ]			
Amendment	0.005 (0.003)	0.026 (0.031)	0.114** (0.058)
Mean of Proportion	0.157		
Observations	72170	72170	72170

*Notes:* The table reports difference-in-differences estimation results using the method proposed by [Callaway and Sant'Anna \(2021\)](#). The dependent variable is the proportion of female workers in column 1, log total employees in column 2, and log total value of output in column 3. Panel A keeps firms having less than 100 employees in the latest pre-treatment period. Panel B keeps firms having between 100 and 300 employees in the latest pre-treatment period. Panel C keeps firms having at least 300 employees in the latest pre-treatment period. The pre-treatment period is defined as less than year 2014 for the control states and less than the year of treatment for the treated states. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are wild-bootstrapped and clustered at the state level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Annual Survey of Industries 2009-2019.

Table A.16: Firm Size and Available Amenities

	Child Care	Free Transport	Health Insurance	Job Training	SoftSkill Training	Cafeteria	Educ Assistance	Work_From Home
11-50	-0.032* (0.017)	0.003 (0.016)	0.118*** (0.014)	0.101*** (0.013)	0.081*** (0.014)	0.060*** (0.016)	0.052*** (0.017)	0.136*** (0.016)
51-200	0.067*** (0.017)	0.169*** (0.015)	0.346*** (0.014)	0.248*** (0.012)	0.247*** (0.014)	0.278*** (0.016)	0.214*** (0.017)	0.269*** (0.015)
201-500	0.268*** (0.017)	0.334*** (0.016)	0.462*** (0.015)	0.332*** (0.013)	0.355*** (0.014)	0.445*** (0.017)	0.383*** (0.017)	0.380*** (0.016)
501-1000	0.413*** (0.018)	0.402*** (0.017)	0.493*** (0.015)	0.346*** (0.014)	0.385*** (0.015)	0.489*** (0.018)	0.455*** (0.018)	0.422*** (0.017)
1001-5000	0.527*** (0.018)	0.449*** (0.017)	0.508*** (0.015)	0.361*** (0.014)	0.405*** (0.015)	0.542*** (0.017)	0.505*** (0.018)	0.458*** (0.017)
5001-10000	0.570*** (0.026)	0.447*** (0.024)	0.501*** (0.022)	0.347*** (0.019)	0.401*** (0.021)	0.532*** (0.025)	0.498*** (0.026)	0.466*** (0.024)
10001 - 50000	0.562*** (0.025)	0.454*** (0.024)	0.508*** (0.022)	0.356*** (0.019)	0.402*** (0.021)	0.525*** (0.024)	0.515*** (0.025)	0.471*** (0.023)
50001 - 100000	0.471*** (0.048)	0.402*** (0.045)	0.471*** (0.041)	0.317*** (0.036)	0.387*** (0.040)	0.511*** (0.047)	0.363*** (0.048)	0.436*** (0.044)
100001+	0.400*** (0.039)	0.389*** (0.037)	0.446*** (0.033)	0.329*** (0.029)	0.350*** (0.033)	0.399*** (0.038)	0.400*** (0.039)	0.433*** (0.036)
Constant	0.273*** (0.016)	0.442*** (0.015)	0.438*** (0.014)	0.610*** (0.012)	0.557*** (0.013)	0.383*** (0.015)	0.398*** (0.016)	0.480*** (0.015)
Mean of DV	.47	.678	.797	.869	.827	.71	.68	.786
R-Squared	.311	.312	.233	.154	.169	.222	.208	.136
Observations	24170	24170	24170	24170	24170	24170	24170	24170
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* The table reports the association between total employees and whether various benefits (across columns) are offered by a firm (indicator variable). Controls include industry type, age, age squared and headquarter country. Mean of DV shows the mean of the dependent variable. Standard errors in brackets are heteroscedasticity robust. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Ambition Box (January 2023).

Table A.17: Firm Size (total employees) and Other Firm Outcomes (ASI data)

	(1)	(2)	(3)	(4)	(5)
	Welfare per employee	PF per employee	Profit per employee	Labor Productivity	Gender Wage Ratio
Panel A: Panel Estimates					
ln(Firm Size)	0.425*** (0.008)	0.381*** (0.009)	1.033*** (0.028)	0.589*** (0.012)	0.001 (0.002)
R-Squared	.765	.823	.504	.714	.543
Observations	864987	864985	812512	864988	192570
Firm FE	Yes	Yes	Yes	Yes	Yes
Indus. $\times$ Yr FE	Yes	Yes	Yes	Yes	Yes
State $\times$ Yr FE	Yes	Yes	Yes	Yes	Yes
Panel B: Cross-Sectional Estimates					
ln(Firm Size)	0.693*** (0.020)	0.784*** (0.020)	0.822*** (0.041)	0.448*** (0.029)	0.002 (0.002)
R-Squared	.388	.385	.0697	.257	.0927
Observations	915211	915209	866096	915212	221948
Indus. $\times$ Yr FE	Yes	Yes	Yes	Yes	Yes
State $\times$ Yr FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

*Notes:* The dependent variables are log transformation of the variables mentioned above each column except profits per employee for which IHS transformation is taken. The variables are defined in Table A.1. Firm size is defined as log of total employees in the enterprise. Controls in Panel B are organisation type, sector (rural/urban) and year of initial production. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted by establishment level survey weights. Standard errors in parentheses are clustered at firm level for Panel A and at state-NIC (4-digit) level for Panel B. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Annual Survey of Industries 1998-2019.

Table A.18: Effect of Amendments on Other Firm Outcomes (DID Estimates)

	(1) Welfare per employee	(2) PF per employee	(3) Profit per employee	(4) Labor Productivity	(5) Gender Wage Ratio
Amendment	0.101* (0.056)	0.090 (0.057)	0.066 (0.149)	0.066 (0.049)	-0.003 (0.008)
R-Squared	.754	.817	.477	.673	.453
Observations	462297	462293	422431	456203	121302
Firm FE	Yes	Yes	Yes	Yes	Yes
Indus. $\times$ Yr FE	Yes	Yes	Yes	Yes	Yes

*Notes:* The table reports difference-in-differences estimation results for the outcome variables in each column using two-way fixed effects. The dependent variable is log welfare per employee, log PF per employee, IHS transformation of profits per employee, log labor productivity (output per employee), and log female to male wage rate, in columns 1, 2, 3, 4 and 5 respectively. Treated states are Rajasthan, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are clustered at the state level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* Annual Survey of Industries 2009-2019.

Table A.19: Firm Size and Gender Wage Gap (Individual Data)

	(1)	(2)	(3)	(4)
	ln(wage)			
6- 10	0.090*** (0.006)	0.083*** (0.006)	0.076*** (0.006)	0.072*** (0.006)
10-20	0.145*** (0.007)	0.133*** (0.007)	0.136*** (0.007)	0.130*** (0.006)
20 and above	0.282*** (0.009)	0.259*** (0.008)	0.266*** (0.007)	0.248*** (0.007)
Female			-0.451*** (0.012)	-0.428*** (0.012)
Female $\times$ 6-10			0.081*** (0.016)	0.064*** (0.017)
Female $\times$ 10-20			0.076*** (0.018)	0.054** (0.019)
Female $\times$ 20 and above			0.131*** (0.022)	0.116*** (0.020)
Constant	5.615*** (0.003)	5.618*** (0.003)	5.694*** (0.003)	5.692*** (0.003)
Mean of DV	480.987	477.682	480.987	477.682
R-Squared	0.621	0.657	0.642	0.675
Observations	300266	293761	300266	293761
District x Yr FE	Yes	Yes	Yes	Yes
Ind x Yr FE	Yes		Yes	
Occ x Yr FE	Yes		Yes	
Ind x Occ x Yr FE		Yes		Yes
Controls	Yes	Yes	Yes	Yes

*Notes:* The dependent variable is log of real daily wage (at 2017 prices) for all columns. Controls include age, age square, education level, religion, social group, sector (rural/urban) and marital status. Mean of DV denotes the mean of the dependent variable without log transformation. The sample includes all individuals working in the non-cultivation sector who work as paid employees. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted by individual survey weights. Standard errors in parentheses are clustered at district level. \*\*\*, \*\*, \* show significance at 1%, 5% and 10%, respectively.

*Source:* NSS rounds 55, 61, 66 and 68, PLFS 2017-18 and PLFS 2018-19.

## B Model: Extension

Here we discuss an alternative version of the model with a *continuum of amenities*, where  $a \in [a, \bar{a}]$  with the following changes from the benchmark: (i) we assume an increasing marginal cost function of producing amenities (ii) the average productivity of male workers is also assumed to increase with better amenities, and (iii) markets are competitive.

The profit function is rewritten as:

$$\pi(z, a) = \max_{N_m, N_f, a} Y(N_m, N_f, a) - w_m N_m - w_f N_f - C(a) \quad (\text{B.1})$$

where

$$Y = z \left\{ (z_m(a) N_m)^{\frac{\sigma-1}{\sigma}} + \tau(z) (z_f(a) N_f)^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\sigma}{\sigma-1}}$$

and  $C'(a) > 0, C''(a) > 0$ . The labor supply function remains the same as Equation 2.

Profit maximization yields the following first-order conditions:

$$N_m : \quad \frac{\partial Y}{\partial N_m} = w_m \quad (\text{B.2})$$

$$N_f : \quad \frac{\partial Y}{\partial N_f} = w_f \quad (\text{B.3})$$

$$a : \quad \frac{\partial Y}{\partial a} = C'(a) \quad (\text{B.4})$$

Substituting the functional forms yields the following:

$$N_m : \quad z \left\{ (z_m N_m)^{\frac{\sigma-1}{\sigma}} + \tau(z) (z_f N_f)^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{1}{\sigma-1}} \left\{ (z_m N_m)^{-\frac{1}{\sigma}} z_m \right\} = w_m \quad (\text{B.5})$$

$$N_f : \quad z \left\{ (z_m N_m)^{\frac{\sigma-1}{\sigma}} + \tau(z) (z_f N_f)^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{1}{\sigma-1}} \left\{ \tau(z) (z_f N_f)^{-\frac{1}{\sigma}} z_f \right\} = w_f \quad (\text{B.6})$$

$$a : \quad z \left\{ (z_m(a) N_m)^{\frac{\sigma-1}{\sigma}} + \tau(z) (z_f(a) N_f)^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{1}{\sigma-1}} \left\{ (z_m N_m)^{-\frac{1}{\sigma}} N_m z'_m(a) + \tau(z) (z_f N_f)^{-\frac{1}{\sigma}} N_f z'_f(a) \right\} = C'(a) \quad (\text{B.7})$$

With the assumption of diminishing returns to effective male and female labor, as firm productivity increases, their demand for effective labor increases for the given wage rates. As seen from equations B.2 and B.3, this results in an increase in both male and female workers. Thus, firm productivity is positively related to firm size.

If the production function exhibits diminishing returns with respect to the effective male and female labor, and average productivity exhibits diminishing returns with respect to changes in amenities, the LHS of equation B.7 decreases for higher amenities. As firm productivity increases, the increased demand for effective labor incentivizes firms to provide higher amenities. Thus,  $a$  is positively associated with firm productivity,  $z$ , which in turn increases with firm size.

Combining equations B.5 and B.6 yields the below relative demand function:

$$\frac{\tau(z) (z_f N_f)^{-\frac{1}{\sigma}} z_f(a)}{(z_m N_m)^{-\frac{1}{\sigma}} z_m(a)} = \frac{w_f}{w_m}$$

From the labor supply function,

$$\frac{w_f}{w_m} = \left\{ \frac{N_f}{N_m} \frac{k_m}{k_f a^\rho} \right\}^{\frac{1}{\epsilon}}$$

In equilibrium,

$$\begin{aligned} \frac{\tau(z) (z_f N_f)^{-\frac{1}{\sigma}} z_f(a)}{(z_m N_m)^{-\frac{1}{\sigma}} z_m(a)} &= \left\{ \frac{N_f}{N_m} \frac{k_m}{k_f a^\rho} \right\}^{\frac{1}{\epsilon}} \\ \implies \frac{N_f}{N_m} &= \left\{ \tau(z) a^{\frac{\rho}{\epsilon}} \left( \frac{z_f(a)}{z_m(a)} \right)^{1-\frac{1}{\sigma}} \left( \frac{k_f}{k_m} \right)^{\frac{1}{\epsilon}} \right\}^{\frac{\sigma\epsilon}{\sigma+\epsilon}} \end{aligned} \quad (\text{B.8})$$

$$\frac{w_f}{w_m} = \left\{ \left\{ \tau(z) a^{\frac{\rho}{\epsilon}} \left( \frac{z_f(a)}{z_m(a)} \right)^{1-\frac{1}{\sigma}} \left( \frac{k_f}{k_m} \right)^{\frac{1}{\epsilon}} \right\}^{\frac{\sigma\epsilon}{\sigma+\epsilon}} \frac{k_m}{k_f a^\rho} \right\}^{\frac{1}{\epsilon}} \quad (\text{B.9})$$

As  $z$  increases, i.e., as firms grow larger, which corresponds to a subsequent increase in amenities provided, even if the relative importance of female labor in production ( $\tau$ ) remains

unchanged, the ratio of female to male workers will increase if the female average productivity response to amenities is higher than men. If  $\tau$  increases with firm size, there is a further shift towards female employees. If  $\tau$  decreases with firm size, the proportion of female employees increases with firm size if the overall effect of amenities on average productivity dominates. As in the benchmark model, the gender wage ratio will increase or decrease with firm size depending on the relative strengths of the productivity channel relative to compensating differentials.

## C Descriptive Evidence: Estimation Strategy

### C.1 Firm-level data: ASI

We use the below specification to examine the association between firm size and female employment using the ASI data:

$$Y_{ijst} = \gamma_0 + \gamma_1 \ln(\text{Firm Size})_i + \delta_i + \delta_{jt} + \delta_{st} + \epsilon_{ijst} \quad (\text{C.1})$$

where  $Y \in \{\text{proportion of female workers, proportion of female mandays}\}$  in firm  $i$ , in industry  $j$  in state  $s$  in year  $t$ . The main independent variable of interest is  $\ln(\text{Firm Size}) \in \{\log \text{ of total employees, log of total output}\}$  in a firm.<sup>1</sup>  $\delta_i$  are firm fixed effects that account for firm-level unobservables that do not change over time like enterprise type (public vs. private enterprises) or gender of the owner, or cultural factors related to firm's location,  $\delta_{jt}$  are the industry (4 digit) times year fixed effects which control for industry-specific changes over time, and  $\delta_{st}$  are the state times year fixed effects. The main coefficient of interest is  $\gamma_1$ , which shows the relationship between a one percent increase in firm size and the percentage point increase in the proportion of female workers. Thus, the specification allows us to examine the association between the percentage of female workers and firm size after accounting for firm-level unobserved factors and industry and state-specific factors. Additionally, we also estimate a cross-sectional specification without firm fixed effects in equation C.1. We additionally control for organization type, rural/urban location, and initial year of production ( $X_{ijst}$ ). All regressions are weighted by the provided probability weights. The standard errors are clustered at the firm level for the panel estimates and state-NIC level for cross-sectional

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<sup>1</sup>When employment variables are used to define firm size, we use  $\ln(0.1+y)$  and rescale by 10 before IHS transformation. For the rescaling, we follow [Bellemare and Wichman \(2020\)](#), which shows that the Inverse Hyperbolic Sine (IHS) Transformation of the variables can affect the magnitude of the elasticity. It recommends that the value of the IHS transformed variable before the transformation should preferably be above 10 for reliable elasticity estimates. If this is not the case it recommends rescaling the variable before the transformation such that it is more than 10. Using similar arguments, the log transformation of a variable after adding a small value is also likely to be sensitive to the value that is added. We then use a similar rule of thumb here.

estimates.<sup>2</sup>

## C.2 Individual data

We estimate the below specification using individual-level employment data.

$$Y_{ijndt} = \alpha_0 + \sum_{s=1}^3 \alpha_s Firm\ Size(s)_i + \beta_4 X_{ijndt} + \delta_{dt} + \delta_{jt} + \delta_{nt} + \epsilon_{ijst} \quad (C.2)$$

where  $Y_{ijndt}$  takes a value of one if individual  $i$  in occupation  $j$  in industry  $n$  in district  $d$  in year  $t$  is female and zero otherwise.  $Firm\ Size(s)$  is a set of dummy variables, such that  $Firm\ Size(1)$  takes a value of one if firm size is 6-9 employees,  $Firm\ Size(2)$  takes a value of one if firm size is between 10-19 employees and  $Firm\ Size(3)$  takes value of one if firm size is more than 20 employees.  $X_{ijndt}$  are control variables for age, age squared, education, religion, caste, marital status, and rural-urban location of the household. As previously, we control for unobservables that can affect the proportion of female workers across industries and location –  $\delta_{dt}$  and  $\delta_{nt}$  refer to district by year and industry by year fixed effects, respectively.<sup>3</sup> Additionally, the individual level data also record the occupation of work. Hence, we control for  $\delta_{jt}$ , occupation by year fixed effects, to absorb any variation in the proportion of female workers by firm size arising from differential task requirements as firms increase in size. If bigger firms differ from smaller firms only in terms of tasks, and relatively more women work in tasks that bigger firms require, the positive relationship should no longer hold between firm size and relative female employment. All regressions are weighted by the probability weights provided in the survey, and the standard errors are clustered at the district level. The

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<sup>2</sup>Since the proportion of female workers is a fractional variable, one can also consider estimating the above specifications using non-linear models for fractional logit. However, given the extensive number of fixed effects in our estimation strategy, these methods are computationally intensive and do not converge in our case. Additionally, [Papke and Wooldridge \(2008\)](#) show that when the estimate of interest is the marginal effect, then there are no significant differences between fractional logit and a linear estimator such as a fixed effects model with a continuous outcome variable.

<sup>3</sup>Over time, state and district boundaries have changed in India. Thus, we combine the new states and districts with the parent states and districts from which they were created in order to maintain a consistent set of state and district codes across years using the administrative boundaries in 1999.

main coefficients of interest here are  $\{\alpha_3, \alpha_2, \alpha_1\}$ . For instance,  $\alpha_1$  indicates the difference in probability of female vs. male employment across firms employing 6-9 workers vs. firms having 1-5 workers. An increase in firm size would be associated with a larger probability of female employment when  $\alpha_3 > \alpha_2 > \alpha_1$ , and all of them are positive in sign.

## **D Audit Study Experiment**

To explore whether gender-based discrimination varies by firm size in India, we undertook a correspondence study across four selected job roles– BPO, Finance, HR and Sales & Marketing. These roles were selected since the job ads within them formed the largest proportion on India’s topmost platform for job search. We created eight fictitious profiles – two per role, one male and one female. These were created to have equivalent qualifications and experience and be similar in every aspect except gender. These profiles were used to systematically apply to job postings for three months, during consistent timings on weekdays. We detail the process of profile creation, job selection, application, and recording callbacks from employers below.

### **D.1 Creating Fictitious Profiles**

To construct our candidate profiles, we drew upon real resumes from subscription-based online databases to ensure that the profiles resembled those of contemporary, actual job seekers in the market. The broad sections and sub-headings remained consistent across all profiles, with slight variations in the order of sections, font choices, text alignment, and other formatting details. The overall aesthetic quality remained similar across CVs. The content within each sub-heading – educational qualifications, title and description of previously held jobs, key areas of competencies and technical skills – was carefully crafted to convey the same qualifications and experience across all profiles. This approach allowed us to standardize the substance of the applications. All the profiles were reviewed by an HR recruiter before the experiment and were deemed similar across three parameters of quality, content, and skills (when name was removed from the CV).

For the HR profiles, we assigned educational qualifications of a BA (Bachelor of Arts) and an MBA (Masters in Business Administration) in HRM (Human Resource Management). The finance profiles had a B.Com. and Chartered Accountant (CA) certification. For the

Sales & Marketing profiles, candidates had completed a Bachelor in Business Administration (BBA), followed by an MBA degree. The BPO profiles, on the other hand, indicated a BA in History. While the colleges across the profiles were different, they were selected to be similar in terms of quality and ranking so that it gave similar signals about the ability of candidates.

Both male and female profiles for a given role had similar ages, but the age varied slightly across roles based on education completion time. The HR and Sales profiles were aged 26 years, the BPO profiles were aged 24, and the Finance profiles were aged 28. Each profile had approximately three years of work experience and was based in Delhi but open to relocating to major cities across the country (Delhi/NCR, Hyderabad, Bengaluru, Mumbai, Chennai, Pune, Kolkata). To maintain consistency, we specified a notice period or earliest possible joining date as one month from the receipt of an offer. We attached a unique phone number and email address to each profile, which was prominently displayed on their CVs. The first and last names were selected to avoid signaling any socio-economic differences, with all profiles indicating upper-caste Hindu backgrounds.

## **D.2 Selection of Jobs**

We developed an algorithm that scraped the details of the posted jobs in the four roles. We filtered active job openings based on the criteria of experience, location (Delhi/NCR, Hyderabad, Bengaluru, Mumbai, Chennai, Pune, Kolkata), and skills. The job ads mentioned the minimum and maximum years of experience expected from applicants. As our profiles had 3 years of experience each, we only applied to job ads that had 3 years included within the range of expected years of experience. We dropped job ads if none of the technical skills mentioned on the job ad matched with skills on our profiles. Lastly, in order to minimize any potential penalty from a company for not responding to interview invitations, we applied to no more than three openings per company.

To obtain the firm size of the employer posting the job ad, we developed a program to scrape firm size information (number of employees) from another online platform called

*AmbitionBox*, which displays the latest firm size for a given company name. The firm sizes are displayed in ranges. The final set of job ads included those for whom we successfully obtained the firm size information.

### **D.3 Applying to Jobs**

To facilitate the application process, we developed an algorithm that scraped the application link and job details and automatically applied for jobs. We created a roster of relevant and active job openings within each sector twice a week and sent out applications between June 17, 2024, and September 17, 2024, on weekdays. For each job opening within a specific role, the algorithm randomly selected one profile (either male or female) to submit first, followed by the other. This randomized order maintains a balance in the application order across profiles so that the order does not end up affecting the study.

### **D.4 Recording Responses to Applications**

We tracked responses to each job application through 3 modes- phone calls and texts, emails, and notifications from the platform. Using the job title and company name provided in these communications, we were able to match the response to the corresponding job application. A job application was considered to have received a callback if the employer provided a positive response through any of the aforementioned channels. Whenever the candidates were invited to interviews or asked to confirm their availability, we politely declined, explaining that the candidate had recently accepted another job offer. We recorded responses from June 17th, 2024, to October 11, 2024.

### **D.5 Callback and Response Rates**

The total number of applications sent was 9238 (4619 for men and 4619 for women). Appendix Table [D.1](#) reports the callback rate, calculated as the proportion of positive callbacks received

to the total number of applications sent ( $\frac{\text{Number of Positive Callbacks}}{\text{Number of Applications}}$ ). The overall callback rate for women across all roles is 3 percent, compared to 3.8 percent for men. A pairwise t-test confirms that this difference is statistically significant. We submitted 800 applications to the BPO role, 1,974 to Finance, 1,918 to HR, and 4,846 to Sales and Marketing. The table shows that women generally receive a lower callback rate than men across all roles except HR, where the callback rate is slightly higher for women. This is in alignment with findings from previous studies, which have also indicate that women are often preferred for female-dominated sectors. In the BPO sector, a gender neutral job role, the callback rate for women equals men. On average, smaller firms have higher callback rates than bigger firms – possibly because bigger firms receive more applications since candidates may find them more attractive.<sup>1</sup> Notably, female profiles with similar skills are less likely to receive a callback from larger receive compared to comparable male profiles (1 percentage point lower callback rate).

We check the above findings using a regression specification that controls for job ad level unobservables. In the first specification, we measure discrimination against women in terms of the callbacks received in the first stage of the hiring process.

$$CB_{i,j} = \beta \text{Female}_i + \gamma_j + \epsilon_{i,j} \quad (\text{D.1})$$

where,  $CB_{i,j}$  is a binary dependent variable that takes the value 1 if the application from profile  $i$  to job  $j$  received a positive callback in the hiring process, and 0 otherwise. The key explanatory variable is  $\text{Female}_i$ , which equals 1 if the profile  $i$  is female and 0 if male.  $\gamma_j$  represents job fixed effects, accounting for characteristics specific to each job that might influence callback rates.  $\beta$  captures the effect of being female on the probability of receiving a callback. Standard errors are clustered at the job-ID level.

The results in the Appendix Table D.2 indicate that across all roles, female profiles are less likely to receive a callback by 0.8 percentage points. This lower callback rate for women

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<sup>1</sup>In terms of posted wages, the average wages across the three firm size categories 1-50, 51-200, and more than 200 were 500,000 INR, 490,000 INR, and 560,000 INR, respectively. The salary differential only seems to arise from the largest category, while the first two firm size categories are similar to each other.

is driven by the Sales and Finance sectors. To also understand the heterogeneity in the level of gender discrimination by firm size, we estimate the following specification.

$$CB_{ij} = \alpha_1 Female_i + \sum_{j=2}^3 \delta_j \cdot (Female_i \times Fsize_j) + \gamma_j + \epsilon_{ij} \quad (D.2)$$

where,  $Fsize_2$  is an indicator variable that takes a value of 1 for firms with 51-200 employees and  $Fsize_3$  is an indicator variable that takes a value of 1 for firms having more than 200 employees. The model thus allows us to examine how callbacks vary across more granular firm size categories and by gender.  $\delta_j$  gives the differential effect on female callbacks in firm size category  $j$  relative to firms having 50 employees or less.

The estimates in Appendix Table D.3 show that female profiles receive a lower callback in larger sized firms compared to smaller firms vs comparable male profiles. This is driven by the BPO role. In other roles, while the direction of the effect is similar, the larger gender gap in the callback rates is not statistically different by firm size.

Table D.1: Mean Callback Rates by Female Profiles

Variable	(1) Female Mean/(SE) [4619]	(2) Male Mean/(SE) [4619]	(1)-(2) Pairwise t-test Mean difference
All Jobs	0.030 (0.003) [4619]	0.038 (0.003) [4619]	-0.008**
<b>Industry:</b>			
BPO	0.065 (0.012) [400]	0.065 (0.012) [400]	0.000
Finance	0.020 (0.005) [837]	0.029 (0.006) [837]	-0.008
HR	0.020 (0.005) [959]	0.019 (0.004) [959]	0.001
SM	0.031 (0.004) [2423]	0.045 (0.004) [2423]	-0.014**
<b>Firm Size:</b>			
1-50	0.068 (0.011) [497]	0.058 (0.011) [497]	0.010
51-200	0.033 (0.005) [1316]	0.046 (0.006) [1316]	-0.012
Above 200	0.021 (0.003) [2806]	0.031 (0.003) [2806]	-0.010**

*Notes:* This table displays the callback rates for men and women for jobs across all industries (first row), followed by callback rates for men and women in every specific industry. It also reports the callback rates for men and women for jobs falling under specific firm size categories. Callback rates are calculated as  $\text{CallbackRate} = \text{Total positive callbacks} / \text{Total applications}$ . \*\*\*, \*\*, \* show significance of the t-statistics at 1%, 5% and 10%, respectively.

Table D.2: Callback rates across industries

	(1)	(2)	(3)	(4)	(5)
	Overall	BPO	Finance	HR	SM
Female	-0.008*** (0.002)	0.000 (0.013)	-0.008* (0.004)	0.001 (0.003)	-0.014*** (0.004)
Outcome Mean	.0341	.065	.0245	.0193	.0382
R-Squared	.785	.712	.838	.904	.768
Observations	9238	800	1674	1918	4846
Job FE	Yes	Yes	Yes	Yes	Yes

*Notes:* The table shows the effect of the applicant's gender on the likelihood of receiving a callback, with results reported across different industries (BPO, Finance, HR, and Sales Management). The dependent variable is a binary indicator, taking the value of 1 if the job application received a positive callback and 0 otherwise. The explanatory variables include 'Female', which indicates whether the applicant is a woman. Standard errors, shown in parentheses, are clustered at the job-ID level. Significance is indicated by \*\*\*, \*\*, and \* for 1%, 5%, and 10% levels, respectively.

Table D.3: Effect of Firm size and Gender on Callbacks for Job Applications

	(1)	(2)	(3)	(4)	(5)
	Overall	BPO	Finance	HR	SM
Female	0.010 (0.010)	0.111** (0.047)	-0.000 (0.016)	0.009 (0.015)	-0.004 (0.016)
Female $\times$ Fsize= [51 – 200]	-0.022** (0.011)	-0.111* (0.058)	-0.020 (0.019)	-0.005 (0.016)	-0.012 (0.017)
Female $\times$ Fsize> 200	-0.020* (0.010)	-0.130*** (0.049)	-0.004 (0.016)	-0.010 (0.015)	-0.010 (0.016)
Outcome Mean	.0341	.065	.0245	.0193	.0382
R-Squared	.00502	.719	.839	.904	.768
Observations	9238	800	1674	1918	4846
(Female) + (Female $\times$ Fsize= [51 – 200])	-0.012** (0.005)	0.000 (0.034)	-0.020* (0.010)	0.004 (0.007)	-0.016** (0.007)
(Female) + (Female $\times$ Fsize> 200)	-0.010*** (0.003)	-0.018 (0.014)	-0.004 (0.004)	-0.002 (0.002)	-0.014*** (0.004)
Job FE	Yes	Yes	Yes	Yes	Yes

*Notes:* The table shows the effect of the applicant's gender and the firm size of the posting company on the likelihood of receiving a callback, with results reported across different industries (BPO, Finance, HR, and Sales & Marketing). The dependent variable is a binary indicator, taking the value of 1 if the job application received a positive callback and 0 otherwise. The explanatory variables include 'Female', which indicates whether the applicant is a woman, and 'Firm Size' (Fsize), a categorical variable with three levels. The base category represents firms with fewer than 50 employees, while the second level corresponds to firms with 51–200 employees, and the third level includes firms with more than 200 employees. Standard errors, shown in parentheses, are clustered at the job-ID level. Significance is indicated by \*\*\*, \*\*, and \* for 1%, 5%, and 10% levels, respectively.