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

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Abstract

Using firm and individual-level data, we provide reduced-form evidence suggesting a positive relationship between relative female employment and firm size. We then use a difference-in-difference strategy exploiting a natural experiment in Indian labor law amendments that raised firm size thresholds for regulatory compliance. We document a resulting 4.2% increase in female worker share in the treated states, along with a 5% and 15% rise in employment and output, respectively. Larger firms providing amenities like maternity benefits, transport, and paid leave, valued more by women, likely drive these results. Our findings suggest that policies promoting firm growth can enhance female employment.

JEL Codes: J16, J18, L25

Keywords: Employment, gender, firm size, labor laws

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1 Introduction

The female labor force participation (FLFP) rate varies from 52% in the OECD countries to 22% in South Asia. Existing literature largely discusses the role played by income, education and social norms as potential explanations behind the variation across countries and even across households within a country. Differential demand for women due to variation in firm attributes, which can also constrain the availability of suitable labor market opportunities for women, however, has received far less attention.

Cross-country evidence shows a significantly positive association between FLFP and firm size (Appendix Figure A.1, Panel (a)), even after accounting for the effects of income (Panel B).[1] If job attributes between small and bigger firms systematically differ such that jobs in bigger firms are more attractive for women in comparison 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 25-30% (ILO estimates) and a country dominated by small firms – almost 75% of the non-farm workforce in India is employed in firms sized less than 10 (Figure A.2)[2]

Using firm-level data from the Annual Survey of Industries (ASI) from 1998-2019, a nationally representative panel data on registered (or formal) manufacturing establishments in India we find a positive relationship between relative female employment changes and firm size, as illustrated in Figure 1. Controlling for unobserved heterogeneity at the establishment level and industry and state level over time, we continue to find a significant positive elasticity

[1]The figures plot data for 156 countries using data from OECD report, World bank Enterprise Data for firm size in formal sector and Our World in Data for FLFP rates. Total countries are 156. The elasticity estimate between FLFP and firm size using the cross-country data is 0.16.

[2]This proportion stands at 20% for the US (Current Population Survey 2000-2021).

of 0.22 between firm size (measured as the total number of hired workers) and the proportion of hired female workers. This positive relationship is statistically significant and robust to using alternative definitions of relative female employment (proportion of female worker mandays and presence of female workers), alternative definitions of firm size (employees and output), and controlling for firm exports. We also verify the relationship at the firm level using data from the Economic Census of India (1998, 2005, 2013) that captures both the registered and the unregistered sector firms across all industrial sectors - agriculture, construction, manufacturing, and services and nationally representative household surveys from 1999-2019, which records individual employment status and establishment size in the non-farm sector. We find that the reduced form positive relationship persists between firm size and female employment, even after we control for individual-specific characteristics and variation across district-year and industry-occupation-year levels.

Next, we use exogenous variation in labor law amendments in two states of India - Rajasthan in 2014 and Jharkhand in 2017 - to verify whether policies that can potentially spur firm growth can also increase female employment. These amendments increased the firm size threshold for the applicability of the Factories Act from 10 to 20 workers (when power was used) and from 20 to 40 workers (when no source of power was used). The amendment to the Industrial Disputes Act (IDA) increased the threshold for a firm to lay off or retrench workers and close an establishment without prior permission from 100 to 300 permanent workers. These amendments provided a direct incentive for firms to grow beyond the thresholds of 20, 40, and 100 and eased the compliance costs for firms employing less than 40 workers. It also provided establishments that employed between 100 and 300 permanent workers flexibility in hiring and firing workers. These Acts have previously been shown to constrain firm size in India (Amirapu & Gechter, 2020). Additionally, by reducing compliance costs, these amendments can directly lend to increased output and profits and consequently affect the amenities that an enterprise can spend on.

We use a differences-in-differences estimation strategy to estimate the causal impact of the amendments on the proportion of female workers and other firm outcomes. Using an event study design, we confirm the absence of pre-trends in outcomes before the amendments across treated and control states. We find that the proportion of female workers increases by 6.3% in the treated vs. the control states after the amendments (using two-way fixed effects strategy). We also use the recent methods proposed for staggered treatment designs (Callaway & Sant'Anna, 2021) and find an increase in the proportion of female workers by 4.2% after the amendments using the alternative method and find no pre-trends. We also find an increase in the number of female workers, the proportion of female mandays, and the probability of an enterprise hiring a female after the amendments. Further, we show that total workers increase by 5%, and output and profits per employee increase by 15% and 35%, respectively, after the amendments in treated vs. the control states. These results show that policies that enable firms to grow in size or increase their profitability can have a positive impact on female employment.

Lastly, we examine the mechanisms through which larger firms can employ relatively more females. Using a simple theoretic framework, we argue that the following channels can potentially explain the positive relationship – (i) bigger firms provide more non-wage amenities valued more by women, (ii) bigger firms have different task requirements which increase the demand for female labor, and (iii) lower discrimination against women by bigger firms. Using household-level data, we confirm that workers employed in larger firms (20 or more workers) are 70% more likely to get maternity benefits, 45% more likely to get paid leaves, 50% more likely to have a written contract, and 70% more likely to get pension benefits from their employers, vs. workers in firms having less than 6 workers. We also corroborate these findings using crowd-sourced data from employees on an online platform. Additionally, we also find that the labor law amendments led to increased expenditure on employee welfare by establishments. As discussed earlier, higher productivity and profits of bigger firms can lead to greater provision of non-wage amenities by them.

To test the hypothesis regarding the differential task requirements, in the individual-level analyses, we control for the granular occupational content and find that the positive association between relative female employment and firm size persists. Besides, ASI collects data only on manufacturing firms where the variation in tasks is limited, where as we discussed before, the relationship exists. This shows that there exists an explanation beyond the differential task requirements across firm-size distribution such that bigger firms have greater demand for female tasks. Next, we test whether bigger firms discriminate less against women. To do this, we implement an audit experiment by sending identical female and male candidate profiles across four industries in the service sector. While we find that female profiles are overall less likely to receive a callback by 25%, bigger firms are either more likely or equally likely than smaller firms to give lower callbacks to similar female profiles. Additionally, Rebien *et al.* (2020) show that smaller firms are more likely to hire through referrals, while bigger firms use more formal search processes to hire workers. The latter can lead to a more diversified pool of applicants. While this channel can also be at play, and we cannot rule this out, it cannot be the only explanation behind our findings. This is because it cannot explain the larger benefits or amenities valued by women being offered by bigger firms, with profit-maximizing objectives, with no effect on the gender wage differentials. 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. However, we do not find a fall in the profit per employee as firm size increases[3].

Taken together, the above findings indicate that bigger firms can employ more women due to provisions of better non-wage amenities valued more by female employees. A natural next question is why bigger firms provide these amenities. There may be legal requirements behind the provision of these benefits (Goodstein, 1994). For instance, in India, firms with more than 50 employees are supposed to provide creches to their employees; maternity leave provision also kicks in for firms that have at least 10 employees. If legal reasons are the

[3] Also, these initiatives have only gained momentum in the last decade in India. The relationship between firm size and female employment holds with similar strengths both in 1998-2009 and 2010-2019. This shows that DEI initiatives by bigger firms are unlikely to be the main driver behind the obtained association.

only factors behind bigger firms providing these non-wage amenities, then employers can compensate for these by paying lower wages to female workers. However, we do not find evidence of a higher gender wage gap for larger firms. In fact, individual-level data show that the gender gap in wages, if anything, is smaller in larger firms. Our theoretical model shows that a lower gender wage gap in bigger firms is plausible when these firms offer non-wage amenities to attract more productive women. Larger firms, which are more productive, can undertake fixed costs involved with family-friendly policies, and employ more productive women through provision of non-wage amenities which women employees value.[4]

Our work contributes to several strands of literature. First, we contribute directly to the literature on firm-level determinants of female labor demand. Surprisingly, there has been little research in this area – with the most attention paid to the exporting status of a firm. Ozler (2000) finds that export-oriented firms are more likely to employ women. Juhn *et al.* (2014) causally show that new export opportunities in Mexican manufacturing reduced gender inequality in blue-collar jobs in the sector due to technology upgrading. Bonfiglioli & De Pace (2021) also find an increase in employment of women relative to men in white-collar work for exporters as demand for interpersonal skills increased. Banerjee *et al.* (2022) find an increase in the share of female white-collar workers in Chile among exporters in response to a positive trade shock due to greater demand for non-production tasks. In a recent study, Chiplunkar & Goldberg (2021) shows that female shares in employment 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. Reilly & Wirjanto (1999) using cross-sectional data for 97 Canadian firms find no monotonic relationship between firm size and proportion of female employees. Mitra (2003), while documenting a negative relationship between the gender wage gap and firm size for 2240 US professional workers in 1998 also note that in their study sample, women

[4] Extremely large firms can also have dedicated human resource departments which are more likely to develop family-friendly workplace policies (Glass & Estes, 1997).

are more likely to be employed in larger establishments.[5] Thus, our study offers the first comprehensive evaluation of the association between firm size and female employment using nationally representative data, accounting for unobservables at firm, industry, occupation and location levels. We further extend this literature by examining the mechanisms that explain this relationship and causally examine the impact of policy instruments that induce firm growth on the share of female workers.

Second, we contribute to the literature that examines the relationship between firm size and non-wage benefits like job flexibility and security, maternity leave, transport, childcare etc (Bryson *et al.*, 2017). Existing literature for the developed countries shows that employer-provided welfare like child-care assistance (financial assistance for child-care, on-site child care, or information service to access childcare), maternity, parental, and sick-child leave are more likely in firms that have a larger employee size (Den Dulk *et al.*, 2012; Evans, 2002; Hall & Soskice, 2002; Hayghe, 1988). On the other hand, larger firms can also have more inflexible schedules and longer working hours (Shao *et al.*, 2021). Extant evidence shows that women have equal or greater preference for non-pecuniary benefits (Goldin, 2014; Erosa *et al.*, n.d.; Mas & Pallais, 2017; Wiswall & Zafar, 2018). In recent study, Morchio & Moser (2024) explain the variation in gender wage gap across firms through the provision of non-wage amenities by them. We extend this literature by showing how these benefits vary by firm size in a developing country context and assess its implications for female share among employees.

Lastly, while the existing literature studies the effects of labor regulations on employment across countries (Botero *et al.*, 2004; Kahn, 2007) and productivity (Autor *et al.*, 2007; Dougherty *et al.*, 2011), there is no evidence on the effects of labor regulations on relative female employment. Almeida & Carneiro (2009) examines how enforcement of labor regulations affects firm size in Brazil and finds that stricter enforcement of labor laws constrains firm size and increases unemployment. In the Indian context, studies have examined the

[5] Card *et al.* (2016) show that sorting and bargaining effects across firms can explain 20% of the gender wage gap in Portugal, and when describing their sample note that females are more likely to work in larger establishments than men in Portugal (858 vs. 730), allowing for no other controls. In a related study, Carter *et al.* (2003) finds that female presence on boards is positively related to firm size.

impact of amending labor regulations on overall employment and growth since these acts impose substantial costs on firms. Besley & Burgess (2004) show that amendments to the Industrial Disputes Act in India during 1958-1992 in a pro-worker direction led to lower output, employment, investment, and productivity. However, none of these studies examine the effects on female employment. We fill this gap in the literature and show that one of the mechanisms through which relaxing labor regulations, increases female employment is by increasing firm size and productivity.[6]

In general, the literature mostly focuses on policies offering protection or benefits to a certain group of workers, which in some cases have unintended consequences of reducing employer demand for these workers. Studies evaluating the effect of maternity and parental leave, equal pay and anti-discriminatory laws as well as laws that mandate wage transparency on female employment find mixed evidence. In the Indian context, Bose & Chatterjee (2024) find a reduction in female employment due to Maternity Benefits Act passed in 2017 (MBAA). Bhalotra *et al.* (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. We extend this literature by showing that policies which are not protective of a group can also spur employment for it.

The rest of the paper is organized as follows. Section 2 proposes a model that motivates our question and provides testable mechanisms. Section 3 provides descriptive evidence on the relationship between firm size and relative female employment. Section 4 evaluates the effect of the labor law amendments. Section 5 discusses potential mechanisms behind our findings. Section 6 concludes.

[6] Studies also examine the impact of state-level variation in labor regulations on firm adjustment to various shocks like trade reforms (Hasan *et al.*, 2007), rainfall variation (Chaurey, 2015; Adhvaryu *et al.*, 2013), dismantling the License Raj (Aghion *et al.*, 2008), among others. See Chaurey (2015) for a review.

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.

2.1 Environment

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. 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.[7]

Each worker receives 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. This assumption is consistent with studies such as Bütikofer *et al.* (2021), which concludes that access to paid family leave improves maternal health.[8] 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 $C > \bar{C}$.[9]

[7]This assumption is consistent with existing evidence (Ngai & Petrongolo, 2017; Olivetti & Petrongolo, 2014)

[8]Similarly, Chowdhury (2018) finds positive effects of on-site childcare on female productivity, Vara-Horna *et al.* (2023) argues that policies aimed to prevent workplace sexual harassment would improve worker productivity and particularly benefit women.

[9]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

A z-productivity firm produces output by hiring N_m male and N_f female workers and providing amenities a using a CES production function, which is described below:

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

Here, τ is the weight attached to the female labor in production. Thus, τ 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 below labor supply curves for men and women:

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

We assume that labor supplied by men and women increases with their wages and the level of amenities. Here, ϵ and ρ 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:

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

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

hold as long as women value amenities more than men.

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 $a \in \{1, \bar{a}\}$.

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

FOC:

$$N_m : \qquad \frac{\partial Y}{\partial N_m} = w_m(N_m) + \frac{\partial w_m}{\partial N_m} N_m \tag{5}$$

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

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. Finally, substituting for the assumed functional forms, the equilibrium female-to-male labor ratio is given by:

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

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 τ) 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 τ 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 τ 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 higher degree of discrimination.

The equilibrium wage ratio is given by:

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

Thus, the gender wage ratio (defined as the ratio of female to male wages) is higher for higher values of τ. 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:

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

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

By the envelope theorem,

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

If τ 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 $\pi(\underline{z}, \bar{a}) - \pi(\underline{z}, 1) < C < \pi(\bar{z}, \bar{a}) - \pi(\bar{z}, 1)$[10], 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 is lower for the larger firms, this effect is amplified, whereas if it is substantially higher, the relationship is reversed.

[10] 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 Descriptive Evidence

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

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).[11] For the purpose of this paper, we use the terms *firm* and *establishment* interchangeably since multi-plant establishments constitute a very small proportion of all manufacturing enterprises in India.[12] The establishment-level ASI data is available from 1998-2019. The ASI provides establishment identifiers for the period between 1998 and 2019. This enables us to undertake both analyses within a firm over time as well as to examine cross-sectional patterns between the variables of our interest.[13]

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.[14] Gender-disaggregated employment data is captured only

[11]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 $1/5^{th}$ units are drawn from each state and 4-digit industry combination based on stratified circular systematic sampling.

[12]For instance, Chakrabati & Tomar (2022) show that multi-plant establishments constitute only 5% 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.

[13]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.

[14]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 ineligible for the benefits and job security available to permanent

for manufacturing workers - including mandays and wages. Since manufacturing workers constitute 72% of all permanent employees (workers, supervisors and other employees), gender-disaggregated data for workers is available for a large proportion of permanent employees in a firm. The survey also provides data on other establishment characteristics like the value of output, input expenditure, including expenditures on employee welfare and contributions towards pension, raw materials, etc., and the value of capital assets. This allows us to examine the relationship between firm size and the proportion of female workers using various definitions of firm size, like employment and output.

Table 1 shows the summary statistics of the main labor market variables. The proportion of female workers is defined as the number of female workers out of the total number of workers. Proportion of female mandays is similarly defined based on worker mandays. On average, women constitute 12% of total workers in manufacturing enterprises. Firm size based on employment can be defined in terms of total workers or all paid employees (workers, supervisors, contract workers, and other paid employees). On average, a firm has 41 manufacturing workers and 76 employees.[15] 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% of the wage rate as men across manufacturing firms.

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, and then it stays almost constant thereafter. This shows that the relationship between

employees.

[15]Figure A.3 shows the firm size distribution for firms across various time spans in our data. Panel (a) defines firm size using total workers, while panel (b) uses total employees. We keep firms with total workers up to 300 in panel (a) and total employees up to 500 in panel (b) since 95% 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% having less than 10 employees.

firm size and relative female workers is non-linear, with the positive association increasing at a decreasing rate with an increase in firm size.[16] We next examine if this relationship holds after controlling for other unobservable characteristics across firms.

3.1.1 Findings: Firm Level

We estimate the relationship between firm size and the proportion of female workers using two specifications (details of the empirical specification are provided in Appendix C). Table 2 shows the relationship between firm size and the proportion of female workers in columns (1), (3) and (5) and on the proportion of female mandays in columns (2), (4) and (6). Panel A reports the results controlling for firm fixed effects (equation C.1). We find that an increase in firm size, defined as the total number of workers, by 1% is associated with a 0.028 and 0.027 increase in the proportion of female workers and mandays in a firm, respectively (columns 1-2). This translates into a 0.22% increase in the proportion of female workers when firm size increases by 1%. The magnitude remains similar when we control for industry and state-specific effects over time in columns (3) and (4). The results in panel B, without controlling for firm-level unobservables, are almost double in magnitude when industry and state-level controls are not included. However, once these are added to the specification, both panel and cross-section estimates are almost similar, showing that industry and location matter the most in explaining the variation of share of female employment at the firm level. In columns (5)-(6), we use a specification that allows for a quadratic in the log of firm size and find that the relationship between the proportion of female workers and firm size is largely positive, with only a slight decline for very large firms. These results show that even after controlling for firm-specific unobservables, industry and location-specific effects, the positive association between firm size and proportion of female workers holds. Additionally, we find that the results persist even when alternative definitions of firm size, such as total

[16]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 northern and southern parts of India. We also find that the relationship is similar across time span.

employees and total output, are used (Table A.1).

We further examine the robustness of our results. We use an extensive margin measure of female employment – whether a female worker is employed in a firm – and again find a significantly positive effect of firm size on the probability of a firm employing a female worker.[17] Appendix Table A.2 shows that the positive relationship between firm size and proportion of female workers holds across both rural and urban areas with slightly higher elasticity estimates for rural areas. Lastly, we also estimate a specification where we divide the firm size into various categories to evaluate the non-linearity in this relationship and report the estimates in Appendix Table A.3. Overall, we see that the increase is sustained and higher firm size categories show a higher proportion of female workers relative to the base group but the increase becomes successively smaller.[18]

3.1.2 Alternate Firm-Level Data: Economic Census

We next examine whether the positive relationship between firm size and the proportion of females hired holds up using the Economic Census of Firms in India, which reports employment data for both registered and unregistered establishments across *all* industries. 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.[19] Table A.4 reports the results for the relationship between the log of firm size and the proportion of females among the employees across all industrial sectors of the Indian economy. Columns (1)-(4) and (5)-(6) report the estimates for the proportion of women among all and hired workers respectively.

[17] The estimates show that an increase in workers (output) by one percent increases the probability of females among the workers by 0.09 percentage points (0.017 percentage points). These results are omitted for brevity but available on request.

[18] We find an increase by 0.052 (43% of mean) in the proportion of female workers in firms sized 10-25 vs. those sized 1-5. The magnitude increases as firm size categories become larger, with an increase by 0.113 (94% of mean) in the proportion of female workers in firms sized > 300 vs. those sized 1-5.

[19] All employees can include household members working in the enterprises as well as other unpaid employees.

We include industry by time and district by time fixed effects to control for variation in female employment across industries/location and over time.[20] The latter sample of workers is comparable with the ASI hired worker sample and hence our preferred outcome variable. We find that a 1% increase in firm size increases the proportion of hired female workers by 0.028 (column 5), with an elasticity of 0.18. This estimate matches closely with the one obtained using the ASI data. The non-linear specification in column (6) shows that the relationship is positive across firm sizes that form a large mass in our data.

We undertake several other checks. Appendix Table A.5 shows that a larger proportion of women are employed by firms in higher-size categories, with the base category of firms having 1-5 workers. Importantly, Appendix Table A.6 shows the results across rural and urban areas for each of the four economic sectors - agriculture (livestock/fishing/forestry/logging), manufacturing, construction, and services. Additionally, we examine the relationship between firm size and the proportion of female hired employees by the gender of the firm's owner since this information is not available in the ASI data. Around 8% of the enterprises are owned by women in India. On average, female-owned enterprises hire more women workers as a proportion of all hired workers – half to 70% (Appendix Table A.7). Theoretically, as discussed in Section 2, lower discrimination, prevalence of basic amenities that women value, as well as the dominance of women-owned enterprises in sectors where women may be higher in demand, can explain the difference.[21] Appendix Table A.7 shows the relationship between firm size and the proportion of female-hired workers for male-owned firms (panel A) and female-owned firms (panel B). The positive relationship is driven by male-owned enterprises. For female-owned enterprises, there is distinct variation across industrial sectors. In agriculture-based enterprises, we see an initial decline in the proportion of female employees

[20] We control for the industry at the most granular NIC available in each round. It is at the 4 digit level for 1998 and 2005 and at the 3 digit level for 2013.

[21] This is possible if women-owned enterprises operate only in certain sectors. For instance, data from the Economic Census show that out of all women-owned enterprises, around 50% are involved in manufacturing tobacco products, 10% in textiles, and 10% in the production of match sticks. On the other hand, 4%, 14%, and less than 1% of male-owned enterprises are in these sectors, with no other sector exceeding 10%. Thus, male-owned enterprises operate across a range of manufacturing products rather than specializing in a select few.

in firms sized 5-10 but thereafter an increase relative to firms having less than 5 employees. For the other sectors, the proportion of female employees decreases with firm size, but the decline is lower for higher firm size categories – giving rise to a U-shaped pattern between the proportion of women workers and firm size for female-owned enterprises[22]. Overall, however, the positive relationship dominates since 92% of the enterprises in India during 1998-2013 were owned by men. Thus, two factors seem to critically affect the female share of workers in firms - firm size and owner's gender (Chiplunkar & Goldberg, 2021).

3.2 Individual Level Data

We use multiple rounds of data from the nationally representative Employment and Unemployment Schedules (EUS) of India's National Sample Surveys (NSS) in 1999-00, 2004-05, 2009-10, 2011-12 (referred to as 1999, 2004, 2009, and 2011 in this paper) and Periodic Labor Force Surveys (PLFS) conducted in 2017-18 and 2018-19 (referred to as 2017 and 2018 in the paper).[23] The PLFS have replaced the NSS since 2017; however, both surveys largely remain comparable in terms of methodology, design, and the variables on which data are collected. Each survey starts from July of the first year to June of the second year, thus covering an entire year.[24] These surveys follow a two-stage sampling design and include repeated cross-sections of households that are selected through stratified random sampling.[25]

They collect information on individual characteristics like age, gender, education, marital

[22]This is consistent with the predictions of the model in Appendix B. Firms that are female-owned may provide some amenities, such as female toilets, workplace safety measures, irrespective of their firm size, and thereby have a higher proportion of women working even at small sizes. As these firms grow larger, the three channels that were discussed before: availability of greater amenities as firm productivity increases, the relative importance of female tasks, and discrimination towards women may interact with each other in a way that explains the overall U-shape

[23]We do not use the NSS survey conducted in 2007 since it does not collect data on firm size.

[24]There is a small difference in stratification in the PLFS - households in villages and urban blocks are additionally stratified on the basis of the general education level of their members. However, this has no bearing on population estimates since all estimates are weighted by sampling weights provided in each round.

[25]In rural areas, the first stratum is a district, and villages are the primary sampling units (PSU) chosen randomly in a district. In urban areas, towns and cities are stratified on the basis of population, and then within each stratum, urban blocks, which form the PSU, are selected using probability proportional to size with replacement. An equal number of households are randomly surveyed in each quarter within each primary sampling unit to ensure equal spacing of observations across the year.

status, employment, earnings and industry and occupation of the employed individuals.[26] For individuals employed in the non-cultivation sector, information on the number of workers in their enterprise, whether the work was full-time or part-time and availability of social security benefits is also provided. The information on firm size is collected at a more aggregate level as compared to the ASI – the respondents choose among the following categories for the number of employees: less than 6, 6-9, 10-19, and more than 20. For our analyses, we consider employed individuals aged 15-65 years at the time of the survey who worked as paid employees. Appendix Table A.8 summarizes the main variables in the individual level data. The proportion of female workers among the paid workers is 19%. Around 60% of the workers are employed in firms having 10 or less employees. Thus, again we observe that micro sized firms constitute a key source of employment in the Indian economy.

3.2.1 Findings: Individual Level

Table 3 reports the estimation results for Equation C.2, where the dependent variable equal one for a female and zero for a male. Columns (1)-(2) report the results for both full-time and part-time workers. Column (1) controls for industry by year and occupation by year fixed effects; Column (2) uses a stricter specification controlling for within-industry variation across occupations in female employment. We find that the probability of a female worker among all workers increases with firm size in both the specifications. Females are more likely to be employed in firms with 10-20 workers and 20 and above workers by 1.9 percentage points (or 10% of mean) and 4.1 percentage points (or 22% of mean) vs. firms with 1-5 workers, respectively (column 2). Columns (3)-(4) report the results for only full-time workers. We continue to find that the probability of a female vs. male worker increases with firm size, even among full-time workers. Women are more likely to be employed full-time in firms with 10-20 workers and 20 and above workers by 12.5% and 28% vs. firms with 1-5 workers, respectively

[26] Our main employment variable measures labor market participation over the reference period of 365 days preceding the date of the survey. An individual is classified as employed if she or he worked for at least 30 days in the preceding 365 days (Usual Principal Activity Status). We choose the yearly reference because firm size information is collected by the surveys for employment recorded under this definition.

(column 4). Thus, the magnitude of the positive relationship between firm size and relative female employment is slightly larger for full-time workers.

The above results show that women relative to men are more likely to be employed in firms of bigger size. This finding holds using both firm and individual employment data, accounting for firm level unobservables as well as occupations or task level variation in relative female employment. Next, we examine whether policies that aim to reduce regulatory requirements in order to promote firm size growth can also have a positive effect on the proportion of female workers. If bigger and more productive firms are more likely to employ women vs. men then we should observe a positive effect of such regulatory changes on relative female employment.

4 Impact of Labor Law Amendments

Regulatory requirements are often regarded as the main hurdle for the growth of the manufacturing sector in India. For instance, the Factories Act and the regulations therein were historically applicable to manufacturing firms with 10 or more workers when the firm used electric fuel power or to firms that employed 20 or more workers without power. Establishments that qualify to be registered under the Factories Act are required to comply with regulations mandated under the law. These regulations are around worker health (cleanliness of the factory, proper disposal of waste, proper ventilation, temperature and lighting, artificial humidification, preventing overcrowding by having only certain number of workers per sq foot of space, accessible toilets), worker safety (fire safety, measures for safety from machinery and chemicals), stipulated working hours with bonus for overtime, and paid annual leave. The only gender specific provision of creches kicks in when number of female employees more than 30.[27] Amirapu & Gechter (2020) estimate the increase in unit labor costs associated with these

[27] Some provisions of the Act only apply to very large establishments. When workers exceed 250 there should be a canteen facility, separate toilets with the number of toilets by sex in ratio of the male and female workers. When workers exceed 150 then adequate and suitable shelters and a lunch room having provision for drinking water.

regulations to be around 35% when the firm size increases beyond 10 workers, thus creating a distortionary effect that incentivizes firms to remain small. Another regulation called the Industrial Disputes Act (IDA) stipulates that any industrial establishment with more than a certain threshold of workers must obtain prior permission from the state government before laying off workers or closing the establishment.[28] Some studies have suggested that the Factories Act, which increases the regulatory compliance costs, and the IDA, which reduces firms flexibility to retrench workers during a negative shock contribute significantly to the small size of firms in India (Hsieh & Olken, 2014).[29]

4.1 Amendments to Labor Laws

States have the power to amend these acts and change the firm size thresholds for their applicability. If these laws restrict manufacturing firms from attaining their true size, then a relaxation in these thresholds should spur firm growth. To examine this, we exploit the amendment to the Factories Act and the IDA in two states of India - Rajasthan, which amended these Acts in 2014, and Jharkhand, which amended them in 2017.[30] These

[28] At this level of threshold (usually 100 for most states till 2013), Amirapu & Gechter (2020) find a smaller increase in unit labor costs when compared to the threshold of 10 workers. A retrenched worker is entitled to compensation equaling 15 days' average pay for each year of service, and for layoffs, every worker is paid fifty percent of basic wages and a dearness allowance for each day that they are laid off (maximum of 45 days). It also requires that firms give sixty days (Section V-A) and ninety days (Section V-B) of prior notification with the government.

[29] Also see: The Economist. A few existing studies find some bunching at the 100-workers threshold but not much, thus arguing that the threshold of 100 for the regulation may not be a binding constraint for firm size (Hsieh & Olken, 2014; Amirapu & Gechter, 2020). However, Padmakumar (2021) argues that lack of bunching at the threshold may not be a sufficient indicator of the distorted policy incentives. It argues that if establishment transitions around the threshold increase when the policy is relaxed also reveals the constraints imposed by it on firm growth.

[30] Jharkhand also amended the Factories Act in 2015, but this was implemented only by December 2016. It amended the IDA in 2016 to increase firm size thresholds for applicability, but this was implemented in 2017. Hence, for Jharkhand, we take the treatment year as 2017 since the on-ground implementation of both amendments occurred in 2017. The state government of Madhya Pradesh also amended the IDA in 2015. However, simultaneously, it also amended the Factory Act to allow women to work night shifts in the manufacturing units. Hence, we drop Madhya Pradesh from our analyses since the amendment of the night shift provision can also lend directly to increasing the hiring of female workers in manufacturing establishments. Other states like Uttar Pradesh and Maharashtra amended the Factories Act firm size thresholds and also amended the night shift rules. These are hence dropped from the analyses. We also drop the small north-eastern states from the analyses, including Assam, due to sample sizes being small and the societal structure being primarily matriarchal. Lastly, we drop Haryana and Andhra Pradesh from our

amendments involved increasing the firm size for the applicability of the Factories Act from 10 to 20 workers when power was used and from 20 to 40 workers when no source of power was used. The amendment to the IDA increased the threshold for a firm to layoff workers and close an establishment without prior permission from 100 to 300 permanent workers. These amendments provided direct incentives for firms under the size of 100 to increase their size beyond the thresholds of 20, 40, and 100. It also provided the establishments that employed between 100 and 300 permanent workers flexibility in hiring and firing workers.[31]

Along with these amendments, Rajasthan also made unionization more difficult. The Contract Labor (Regulation and Abolition) Act was also amended to apply to establishments with 50 or more contract workers from 20 earlier. Both states made violations under the Factories Act non punishable by police arrest upon payment of a fine. Also, complaints against the employer about violation of this Act would not receive cognizance by a court without prior written permission from the State government.[32] Though, as noted in (Bhattacharjea, 2021), not all amendments were pro-employer. For instance, the severance pay was increased by twice the amount, which was a pro-worker amendment. However, these amendments largely relaxed the costs associated with non-compliance at smaller firm size thresholds. If this eases constraints on firm size growth then this could lead to a relatively larger increase in female vs male employment in the states which amended the labor laws. Another channel that can increase relative female employment is overall aggregate increase in demand as new firms enter and less firms exit, and compete for the limited pool of workers. In the next section, we examine whether these amendments played a role in increasing the employment of female workers by spurring firm growth. We discuss whether other channels can also explain

analyses because while we were able to find notifications for amendments, there is no circular available for the exact date of implementation. This makes the legal status of regulations uncertain. We finally have 21 states and union territories in our analyses.

[31] While there should have been a direct effect on the growth of firms sized more than 300, it is plausible that firms just around the cutoff of 300 may have been incentivized to reduce their size to allow themselves the flexibility, but firms beyond the immediate vicinity of the 300 permanent employees cutoff could also gain through the general equilibrium impacts of increased output and employment in the states that implemented the reform.

[32] In Rajasthan, the Apprentices Act, 1961 was also modified with the stipend for apprentices fixed at the minimum wage and the government to bear part of the costs of apprentice training.

our findings).

4.2 Empirical Strategy

We estimate the causal effect of the amendments on firm outcomes from the ASI data on manufacturing firms, using a difference-in-differences strategy. Specifically, we compare the change in outcomes in states that amended the labor laws with states that did not amend them, before and after the amendments, after controlling for firm-specific unobservables, using the below specification:

$$Y_{ijst} = \delta_i + \delta_t + \delta_{jt} + \beta_1 Amendment_{st}^{\tau} + \epsilon_{ijst} \tag{11}$$

where Y_{ijst} refers to the outcome variable for firm i in industry j in state s in year t. Here, τ denotes the relative year, e.g., $\tau = -1$ for the year before the treatment, and t is the actual calendar year. The main variable of interest, $Amendment_{st}$, is an indicator variable that takes a value of one for states that amend the labor laws following the years after the reform (i.e., $\tau \geq 0$) and zero otherwise. We control for establishment (δ_i) and year fixed effects (δ_t) effects to control for unobservables at the establishment and year levels. Additionally, we also control for any change in industry level policies over time on the outcome variables (δ_{jt}). We cluster standard errors at the level of the state since that is the unit of treatment (Bertrand *et al.*, 2004). β_1 gives the average treatment effect (ATE) of labor amendments on firm outcomes. These include proportion of female workers and various firm size measures such as log of workers, employees and output. In our main analyses, we use data from 2009-2019 since variable definitions in the ASI questionnaire, industry and product codes have been consistent after 2008.

While the above specification gives the average treatment effect of the amendments, we also estimate the dynamic treatment effects before and after the amendments. The below event-study specification allows one to check for pre-trends and also to estimate the treatment effects of the amendments exploiting the staggered implementation across the two states:

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

The main variable of interest, $Amendment_s^\tau$ is an indicator variable that takes a value of one for states that amend the labor reforms, τ periods from the amendment, and zero otherwise. We create bins for the endpoints of the event window based on standard event-study applications (Schmidheiny & Siegloch, 2019). We do this at event dates of -4 and 2 and normalize coefficients to event time -1.[33] The year of the amendment is denoted as event time 0.[34]

β_τ measures the average treatment effect on the outcome variables τ periods from the treatment. The event study design allows us to test for common pre-trends directly and to test whether the effects in the post-amendment years differ from these. Specifically, we test whether $\beta_\tau > 0$ for years $\tau \geq 0$ differ from zero. If the amendments increase the proportion of female workers, then β_τ should be positive for periods after the amendment.

A growing literature in the difference-in-differences design highlights the possible bias that can afflict the two-way fixed effects estimator when there is variation in the timing of treatment (Goodman-Bacon, 2021; Callaway & Sant'Anna, 2021; Sun & Abraham, 2021).[35] This is due to two reasons. First, when the treatment effects are dynamic, i.e., they can change over time. In such a case, previously treated units form a bad control group for units that are treated later. Second, the weights attached to the treatment effects depend on the number of periods that a unit is observed as treated. Hence, given that the two states that amended the labor laws during this time period undertook it 3 years apart, it becomes imperative to correct this concern. To account for these issues, we use the estimator proposed

[33] The leads and lags are determined by the treatment years. Given the first treatment occurred in 2014, the maximum number of periods after treatment is five. The second treatment was in 2017, and this makes the maximum number of pre-periods equal to eight. The binning of endpoints at -4 and 2 ensures that both the treated states are included in the pre and post-period event window, respectively.

[34] The common number of pre-periods is four, and post-periods is two, directing our choice of endpoints.

[35] See Roth *et al.* (2022) for a review.

by Callaway & Sant'Anna (2021) since it allows one to directly construct wild-clustered bootstrapped intervals when the number of clusters are small.[36]

4.3 Impact of Amendments

Table 4 shows the impact of the amendments on the proportion of female workers in columns (1)-(2) using equation 11. We find an increase in the proportion of female workers in a firm by almost 0.008 (or 6.3% of mean) when controlling for firm and industry-year fixed effects in column 2. To test the presence of pre-trends and evaluate the dynamic effects over time in the outcome variables due to the policy change, we then estimate the event study in equation 12. Figure 2, panel (a), plots the coefficients obtained using a two-way fixed effects estimator. We find no significant differential trends in the proportion of female workers in the treated states versus the control states before the amendments were passed, but there is a significant positive impact on the proportion of female workers from the year in which the amendments became effective.

As discussed earlier, the positive impact of relaxing labor laws on the proportion of female workers could be driven by an increase in firm size, as firms may find it easier to expand when costly restrictions that become applicable at certain thresholds are relaxed. To check whether the expansion of firm size plays any role in explaining the observed increase in relative female employment, we also estimate the impact of the amendments on various firm size indicators. Table 4, columns (3)-(4) show that total workers increased by 2.6%, employees by 3.6%, and output by 22%. However, the positive effect on workers and employees is noisy. Figure 2, panel (b)-(d), plot the event study estimates for workers, employees and output. These show a significantly positive impact on total workers after the amendments; however, these are not very different from changes before the amendments, leading to an overall insignificant positive effect. Panels (c) and (d) show a positive effect on employees and output, with no pre-trends in these outcomes. We see that the impact on these outcomes is increasing with

[36] We also used alternate estimators such as those by Sun & Abraham (2021) and find similar results to the TWFE estimator, hence, omit them for brevity.

time after the amendments are passed.

Given the staggered implementation of the amendments and the possibility that the TWFE estimators will not be consistent in the presence of dynamic effects, we next use the alternate DID strategy proposed by Callaway & Sant'Anna (2021) to estimate the impact of the amendments on the outcome variables. These estimates use the doubly robust inverse probability weighting with never-treated observations as the relevant control group. We plot the coefficients in Figure 3. We find no differential trends in the outcome variables across treated and control states before the amendments but find a positive impact on the proportion of female workers (panel a) and total workers (panel b) after the amendments. The confidence intervals become slightly larger in this specification, but the causal effect estimated using the alternative method shows a 0.006 increase (or 4.2% over the mean) in the proportion of female workers, statistically significant at the 5% level. The total number of workers significantly increase by 5% and output by 15% (panel d) after the amendments. However, the positive effect on total employees is not significant at conventional levels. Importantly, we do not find pre-trends in any of the outcome variables. Thus, the overall effects taking into account the staggered implementation, in fact, are statistically stronger though slightly attenuated in magnitude than the two-way fixed effects estimator. Taken together, these results show a significantly positive impact of the amendments on the relative employment of female workers. One of the channels behind this effect is plausibly increased firm size in the states that amended the labor laws, with a stronger effect on output than employment.[37] These results show that policy reforms that aid firm growth can also increase female employment.

4.3.1 Robustness

We first examine the effect of the amendments on alternate measures of female employment. Appendix table A.9 reports the overall difference-in-differences estimates using the TWFE

[37]Notably, we also find a positive effect raw materials used in production which increase 26% after the amendments. On the other hand, we find a 2.9% increase in capital expenditure by firms, however this is insignificant. This shows that firms expanded their output by increasing use of labor and raw materials, rather than capital.

strategy for the extensive margin measure of female employment (whether a female is employed by an establishment) in column (1), log of female workers and male workers as the measure of overall female and male employment in a firm in columns (2) and (3), respectively and on the proportion of female mandays in column (4). We find that there is an increase in the probability of female employment in a firm by 3.4 percentage points. Given that 33 percent of firms employ women in our data, this is an increase of 10% in the probability of female employment. The results in columns (2)-(3) indicate that the increase in the proportion of female workers is driven by a significant and relatively larger increase in female workers than male workers. Lastly, we also find an increase in the proportion of female mandays in a firm after the amendments by 0.009 (or 6.7% of mean). Additionally, we examine the heterogeneity in the effects on rural vs. urban areas and find a similar increase in both (column 5). Next, we use sample weights associated with firms which are not surveyed every year in the ASI and report the results in Appendix Table A.10, Panel (a).[38] We find that our results continue to hold with sampling weights as well. We also consider the entire data from 2001-2019 in our analyses and report the estimates in panel B.[39] Our findings continue to hold. Panel (c) includes all treated states that amended and notified the change in thresholds for the Factories Act and also extended the provision to work during the night shifts to women. As expected, our results are even stronger in this specification, with an increase in both the proportion of female workers and in firm size in the states that amended the Acts.

Lastly, to address any concerns that differences in firm characteristics could drive our findings, we match the firms in the control states with the firms in the treated states using propensity scores with the nearest neighbor matching method. We match on baseline characteristics of firms – industrial code (3-digit), organization type, firm age (average in the pre-period), and sector (rural/urban). Appendix Table A.11 shows the estimates for the proportion of female workers (column 1) and various measures of firm size (columns 2-4). We

[38] We do not use weights in the main DID estimates so that they are comparable to the staggered event study design by Callaway & Sant'Anna (2021) since the staggered design does not incorporate the inclusion of probability sampling weights.

[39] We drop 1998-2000 due to incomplete product coverage in the initial years of the ASI data.

find that the direction of the impacts remains similar. We find a 0.008 increase in female proportion (16% of mean). Workers, employees, and output also increase by 9%, 3%, and 36%, but the estimates are statistically significant for output at 5% level and only marginally significant for total workers at 15% level. The F-stat of the joint test that the baseline characteristics match across the treated and control firms is very small (0.11) showing that the samples match well at baseline after re-weighting.

5 Mechanisms

In this section, we investigate the possible mechanisms behind the observed positive relationship between the firm size and the proportion of female workers. As discussed in Section 2, three channels may explain this relationship: (i) the provision of amenities by larger firms, which are valued relatively more by women, (ii) lower discrimination in the larger firms, and (iii) changes in task requirements across firm size that requires the hiring of more women workers. As seen in Table 3, in the analyses of individual data, the positive association survives after controlling for occupation of work within an industry; this shows that demand for differential tasks cannot be the only explanation behind our findings. Next, we discuss the evidence behind the other plausible channels.

5.1 Amenities

We examine whether bigger firms offer more amenities to employees using the NSS and the PLFS data, which capture a few attributes of the job – availability of part-time vs full-time, written contract, maternity/health benefits, pension, and paid leave. These benefits may be differently valued by gender. For instance, extant literature shows that women prefer part-time work over full-time work. If bigger firms are more likely to offer part-time work, then that may explain some part of the positive relationship between firm size and female employment. Again, if women value maternity benefits provision, then they are more likely to prefer bigger firms if these firms are more likely to offer them.

First, we examine which of these benefits matter for greater female representation across firms using household data. Appendix Table A.12 shows the association between the availability of a particular amenity in the job and the probability of a female worker being employed in a firm that offers it. The dependent variable is whether or not a worker is a female. Columns (1) and (2) successively control for various fixed effects at the industry and occupation level and include other individual controls, along with the five benefits that we have examined earlier. The results show that women are 17 percentage points more likely to work in a part-time job, 2.7 percentage points more likely to work in a firm where a written contract is offered, and 2 percentage points more likely to work in firms where healthcare and maternity benefits are offered compared to men. On the other hand, the availability of old-age support reduces the relative presence of female workers in a firm.[40] The above evidence shows that bigger firms offer higher amenities on average that are valued by women.

Second, Table 5 shows the relationship between firm size and job benefits recorded in the data. Column (1) shows that the availability of part-time work does not change significantly with firm size in India. Hence, this cannot explain the positive relationship.Column (2) shows that a worker is more likely to have a written contract when working in bigger firms. Firms of size 20 or above are 14 percentage points ($\approx 50\%$) more likely to offer a written contract. Column (3) shows that firms of size 6-10, 10-20, and more than 20 are 1.6, 4.7, and 15 percentage points (70%) more likely to offer healthcare and maternity benefits. Bigger firms are also more likely to offer pension benefits (column 4) and paid leave to employees (column 5) by 70% and 45%, respectively. Thus, we find that most benefits, except part-time work, seem to increase with firm size.

Alternatively, we also provide evidence from data on reported benefits by employees on an aggregator platform in India called Ambitionbox. It uses crowd-sourced data from

[40]The number of observations is smaller since information on part-time vs. full-time work is only available for the NSS Survey rounds. Columns (3)-(4) use complete data after dropping the part-time work variable. We find similar results.

employees to gather their reviews about various amenities when these are offered by firms. Appendix Table A.13 shows whether a particular benefit reported as being offered in a given firm is related to the number of employees the firm has in India. Again, we find that bigger firms are more likely to provide child care, free transport, and work from home, apart from other amenities – amenities shown in the literature to be more valued by women (Mas & Pallais, 2017; Wiswall & Zafar, 2018). A firm having 500-1000 employees is almost 40 percentage points more likely to offer these benefits vs. firms having at most 10 employees. This corresponds to almost a 100% increase for benefits such as child care and 60% for free transport. Some of these benefits have been shown to be valued more by women.

While the firm-level data (ASI) does not capture the exact benefits provided by the firm, it records the total welfare expenses by the employer on the employees. These include, for example, expenditure on maternity, creches, canteen facilities, educational, cultural, and recreational facilities, and social security contributions towards old age benefits like provident fund, pension, and gratuity (PF). Both expenditures are deflated using the CPI with the base year as 2004. Table A.14, column (1), panel A, reports the results for the association between the log of per-employee welfare benefits with firm size measured as total employees, exploiting variation in size within a firm over time.[41] We find that an increase in total employees by 1% increases the welfare benefits per employee by 0.42% and per employee pension benefits by 0.38% (column 2, panel A). These positive associations hold in cross-sectional estimates in panel B as well. Thus, while ASI does not capture the exact nature of the benefits – on average bigger firms spend more on welfare per employee than smaller firms.

The theoretical model in Section 2 showed that higher productivity and profits allow bigger firms to provide the amenities. Thus, we next examine the association between other firm productivity and firm size in our data. Here, profits are deflated by two digit industry specific WPI with 2004 as the base year. Total Factor Productivity (TFP) is measured using

[41]We use total employees as the firm size since welfare and provident fund expenditures are captured for all employees and not just for workers. The results are similar when total workers are used to measure firm size instead.

the method described in Levinsohn & Petrin (2003). This is implemented using the procedure provided in Petrin *et al.* (2004). Labor productivity is defined as the total value of real output per employee. Appendix Table A.14, columns (4), (5), (6) estimate the relationship between firm size and profits per employee, labor productivity, and TFP, respectively. We find that there exists a positive relationship between firm size and all three measures of firm productivity for both panel and cross-sectional estimates. The estimates show that profits increase by 1%, labor productivity by 0.58%, TFP by 0.05% when the firm size increases by 1% (panel A). We check the robustness of the above findings by defining firm size using total output (Appendix Table A.15). These results show that bigger firms are likely to have higher profits, which they can use to bear the fixed costs of provision of benefits, especially like creches or transport that women value.

Finally, we examine the effect of the labor law amendments on measures of amenities and firm productivity. Notably, since the amendments also led to a reduction in worker safety and health norms, if such amenities are valued relatively more by women, it could also lead to a reduction in the proportion of female employees. However, allowing firms to grow can enable them to optimally choose the amenities they would like to invest in order to attract workers rather than the external imposition of regulations that often invite harassment by labor inspectors (Amirapu & Gechter, 2020), further increasing costs suboptimally. If the proportion of female workers hired by firms increases after the amendments due to firms offering higher amenities valued by female employees as their size increases, then welfare expense per employee by firms should also increase. The estimates in Table 6 using the TWFE strategy show that welfare and PF per employee increase after the amendments are enacted in the treated states vs. the control states by 23% (column 1) and 5.7% (column 2), respectively. However, for PF, the effect is insignificant. Profits per employee and TFP also increase by 35% (column 4) and 3% (column 6), respectively. We find no significant increase in output per employee (column 5) after the amendments, but the effect is positive and large, showing an 11% percent increase in labor productivity due to amendments. Figure 4 shows the event study estimates for these outcomes using the staggered design. Clearly, there is an increase in welfare expenses per capita (by 13%, significant at the 5% level) after the amendments. There is also a clear increase in profits per employee (by 38%, significant at 1% level), but TFP and labor productivity show an increase 1-2 periods after the amendments are enacted by 2.5% and 9% on average, respectively (significant at 5% level).

Taken together, these results show that an increase in firm size accompanied by higher profits and productivity, after the amendments allow the firms to offer higher non-wage amenities. The higher amenities, as long as valued more by women vs. men, can potentially explain the increase in the proportion of female employees after the amendments observed in Section 4. The higher output and profit growth could be a result of reduced compliance costs as well as increased firm size in response to the amendments. Additionally, the policy could have improved aggregate demand for workers as more firms enter and fewer exit in the treated states, leading to an increased demand for female workers. We find a positive but imprecise effect on aggregate number of firms in states-industry after the amendments (Appendix Table A.16), showing that firm size growth relative to an increase in the number of firms is likely the most important channel behind the observed positive effects of the amendments on the proportion of female workers.

5.2 Discrimination

Another explanation for the increase in the proportion of female workers in bigger firms can be reduced discrimination. One suggestive test for this could be examining the gender wage gap in bigger vs. smaller firms. However, the distribution of worker ability can change across firms (Brown & Medoff, 1989; Eeckhout, 2018; Scoppa, 2014). Specifically, if more productive women than men sort into bigger firms then without controlling for unobservable ability the gender wage gap can be smaller in bigger firms. Second, if bigger firms pay higher benefits that women value more, they can reduce the wages offered to female employees (compensating wage differential). Alternatively, if the provision of benefits is accompanied by higher female labor marginal productivity, then the gender wage gap might reduce with an increase in firm size due to amenities. Thus, exante, the gender wage gap can go in either direction across firm sizes based on which channel dominates.

To check this, we examine the relationship between firm size and wages across gender in Table 7 using the NSS and the PLFS individual employment data. Here, the dependent variable is the log of the daily wage rate.[42] Columns (1)-(2) show a positive association between wage rates and firm size in line with the existing literature, while columns (3)-(4) additionally show the relationship between the gender wage gap and firm size. The results show that bigger firms have a lower gender wage gap (columns 3-4). On average, the daily wage rate earned by women is 42% lower than men. However, women who work in firms of size 6-20 earn 36% lower wages, while those in firms with 20 and above employees receive 30% lower daily wages than men. Thus, the gender wage gap tends to be smaller in bigger firms. While we control for demographic characteristics of women in our individual data (age, education, caste, religion, sector, and marital status), these are unlikely to control for the full extent of the selection effects arising from unobserved ability, and hence, these magnitudes on the gender wage gap should only be taken suggestively. Importantly, we do not find any increase in the gender wage gap (or lower female-to-male wage ratio) with firm size. This points to either lower discrimination or higher ability of women in bigger firms dominating the compensating wage differential channel.[43] The amendments also do not have a robust effect on the gender wage gap (Figure 4, panel (c)).[44] Given that firms find it profitable to provide higher amenities as their sizes grow (as seen in the previous section) and similar or higher relative wages to women, we can argue that lower discrimination in larger firms is not

[42]We construct this by dividing the weekly earnings by the number of days worked by an individual in the last week.

[43]We also examine the relationship between gender wage gap (log of relative female to male daily wage) and firm size in the firm level data and report the estimates in Table A.14, column (3). In panel A, when using firm fixed effects, we find that the female-to-male wage ratio increases by 0.001% when firm size increases by 1%. When examining the relationship using the cross-sectional estimation, we again find an increase in the female-to-male wage ratio by 0.002% when firm size increases by 1%. None of the estimates are significant, though.

[44]In fact, we do not find a significant effect of amendments on overall wage rate paid by the firm.

the only channel at play.

Finally, we also directly conduct an audit study experiment to examine if bigger firms discriminate less against female employees (details provided in Appendix D). We sent two fictitious resumes across four roles – Business Process Outsourcing (BPO), Finance, Human Resources (HR), and Sales and Marketing during June 2024-August 2024. One resume was for a male profile and another for a female profile. They had equivalent qualifications, experience (3 years), and were similar in every aspect like location (Delhi), marital status (married) and age. We applied to job postings on India's largest job portal, during consistent timings on weekdays and randomly chose the date of sending either the male or the female profile. These were sent on consecutive weekdays. Additionally, based on firm name we obtained the number of employees of that firm in India through an online platform called the AmbitionBox. Approximately, 497 firms in our sample had 1-50 employees, 1316 had 51-200 employees, and 2806 firms had >200 employees. We recorded the callback rates for our profiles through phone, email and the online platform. We then examine whether there is a differential rate of receiving a callback by female vs. male profiles and whether this varies by firm size.

Appendix Table D.2 reports the overall and industry level differences in callback rates. Overall, we find that the probability of receiving callbacks is lower for female profiles by 25%. This is driven by male dominated roles like finance and sales/marketing. This is in line with several studies in other country contexts (see Baert (2018) for a review). Next, in Appendix Table D.3 we report the heterogeneity in the callback rates across female and male profiles by firm size categories. The estimates show that overall smaller firms are less likely to discriminate against female profiles. Thus, the level of discrimination, if anything tends to increase with firm size. However, this result is driven by the BPO role. In other roles we do not find significant differences in callback rates across gender by firm size. While this experiment is based on service sector industries, the results show that lower discrimination by bigger employers cannot be the only driver for the higher proportion of female employees at bigger firms, accompanied by a lower gender wage gap. It is likely that bigger firms also attract women of higher ability, or the presence of amenities is more productivity-enhancing for women than men, as outlined in the theoretical model.

6 Conclusion

Using firm-level panel data and individual-level survey data, we find that the proportion of female employees increases with firm size in India. This holds even after controlling for firm-level unobserved heterogeneity, industrial structure, firm location, and occupational variation in employment by gender. To examine this causally, we use exogenous variation in labor law amendments across Indian states, which increased worker size thresholds for their applicability, employing a staggered differences-in-differences estimation strategy. We find that the amendments increase firm size by approximately 5% and the proportion of hired female workers by 4.2%.

Using a simple theoretical framework, we argue that the more productive, larger firms find it profitable to provide better amenities to women. This is because it increases their productivity and their willingness to work, which explains the positive relationship we observe between firm size and relative female employment. We empirically corroborate this by showing that larger firms are more likely to provide maternity benefits, transportation, and job stability (contracts), which, as existing literature suggests, are amenities valued more by women. Women are also more likely to receive them in our data, showing that they may prefer workplaces offering these non-wage amenities. Further, we find an increase in welfare expenses per employee after the labor law amendments in the treated vs. the control states. These results indicate that policies facilitating firm growth can also impact female employment positively as more productive firms are able to invest in amenities that attract women. Importantly, we do not find a higher gender wage gap in bigger firms showing that compensating wage differentials is likely dominated by women's higher productivity in these firms. Finally, we present evidence ruling out task-based explanations and discrimination as the primary channels behind our findings.

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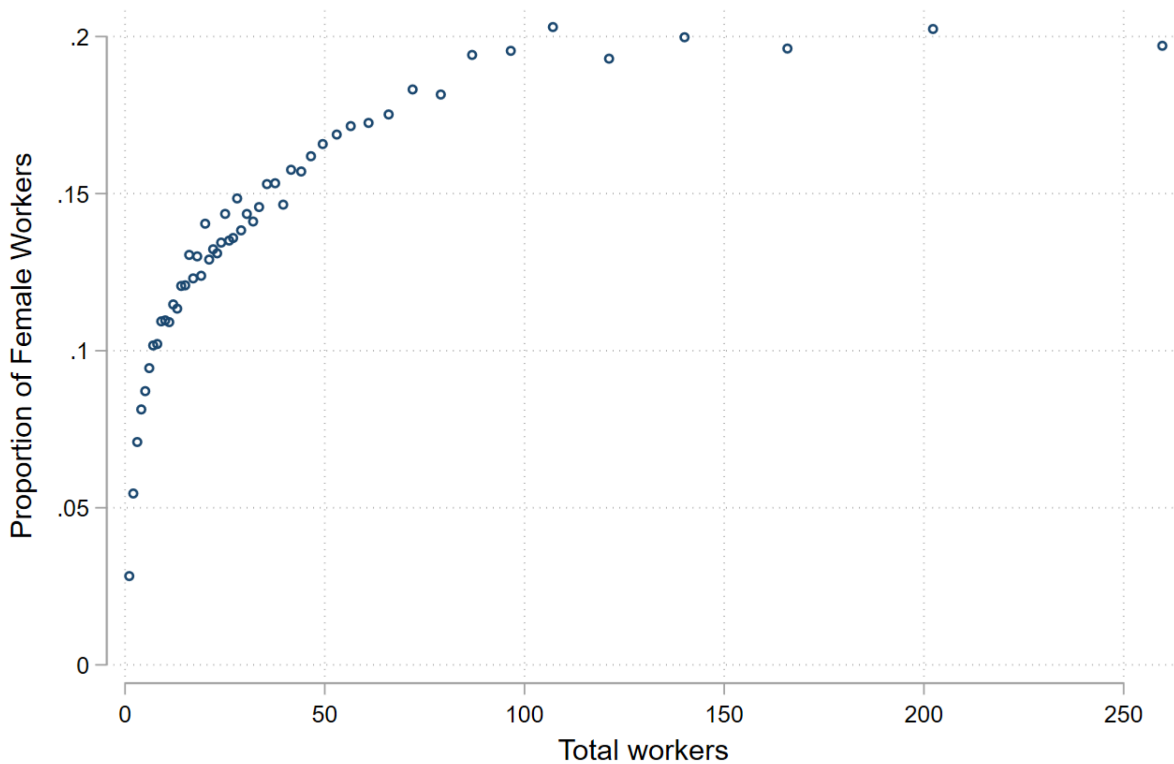
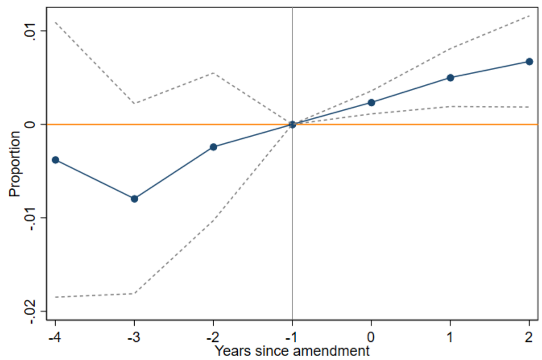
Figure 1: Proportion of Female Workers across Firm Size (ASI data)



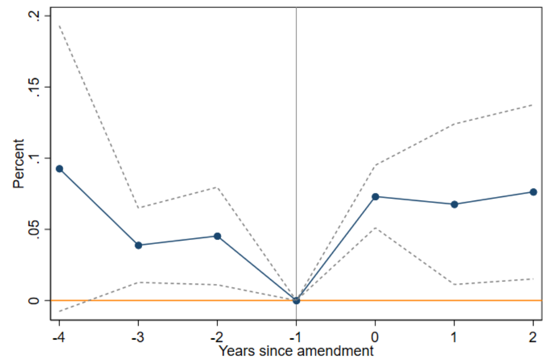
Notes: The figure plots the binscatter between the proportion of female workers and total workers in a firm across all enterprises.
Source: ASI 1998-2019.

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

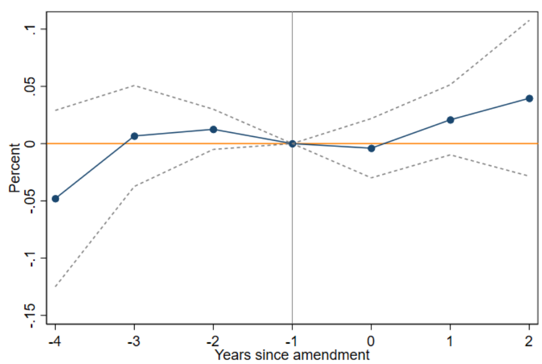
(a) Proportion of Female Workers



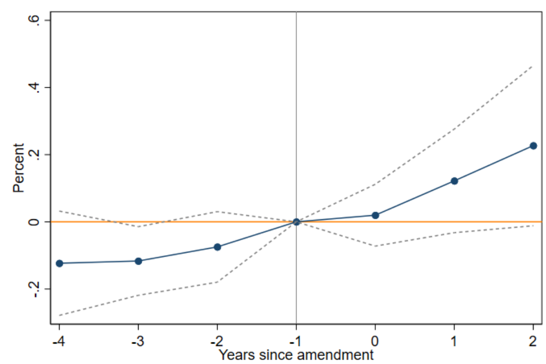
(b) Total Workers



(c) Total Employees



(d) Total Output

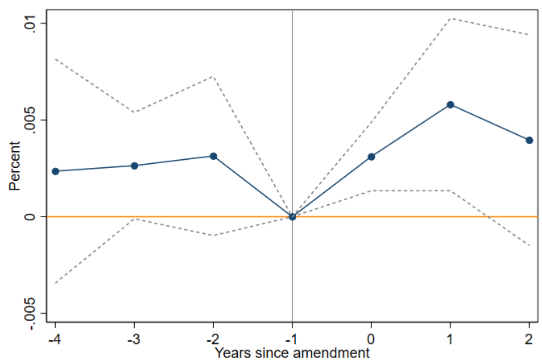


Notes: The above figures show event-study plots estimating the impact of state level amendments increasing the firm-size thresholds for applicability of the Factories Act and the Industrial Disputes Act using the two-way fixed effects estimator. The outcome of interest is the proportion of female workers (Panel a), (logged) number of total workers (Panel b), (logged) number of total workers (Panel c) and (logged) total value of output (Panel d). 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.

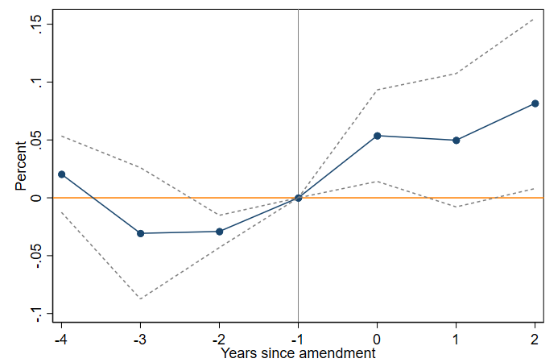
Source: ASI 2009-2019.

Figure 3: Impact of Amendments: Firm size and Female Employment (Staggered Event Study)

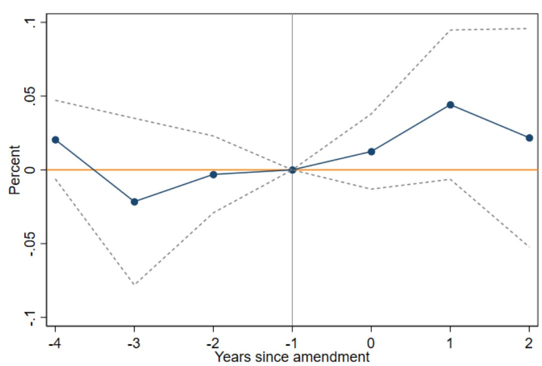
(a) Proportion of Female Workers



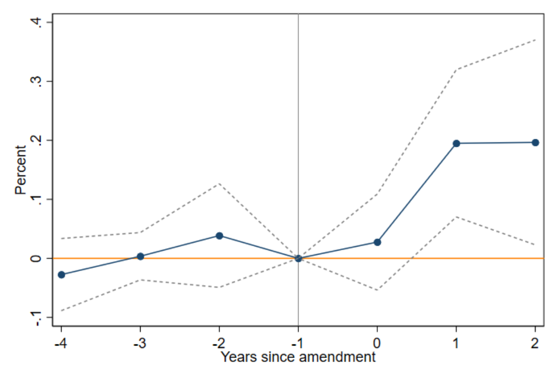
(b) Total Workers



(c) Total Employees



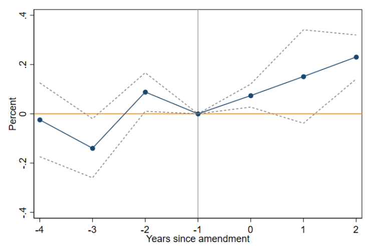
(d) Total Output



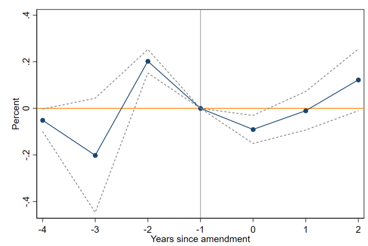
Notes: The above figures show event-study plots estimating the impact of state level amendments increasing the firm-size thresholds for applicability of the Factories Act and the Industrial Disputes Act using the (Callaway & Sant'Anna, 2021) estimator. The outcome of interest is the proportion of female workers (Panel a), (logged) number of total workers (Panel b), (logged) number of total workers (Panel c) and (logged) total value of output (Panel d). 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 clustered by state.
Source: ASI 2009-2019.

Figure 4: Impact of Amendments on Other firm outcomes (Staggered Event Study)

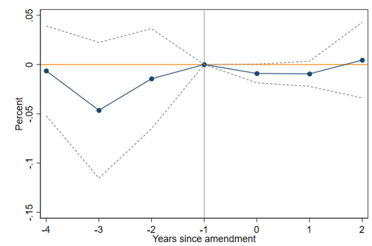
(a) Welfare per employee



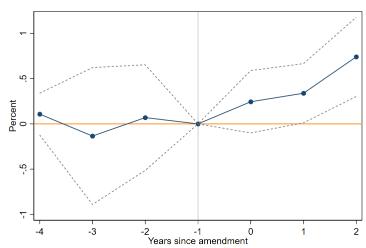
(b) PF per employee



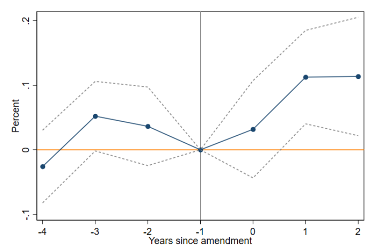
(c) Gender Wage Gap



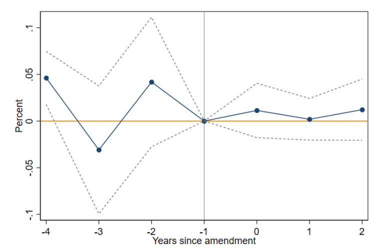
(d) Profit per employee



(e) Labor Productivity



(f) TFP



Notes: The above figures show event-study plots estimating the impact of state level amendments increasing the firm-size thresholds for applicability of the Factories Act and the Industrial Disputes Act 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 log of the female to male wage ratio (Panel c), the IHS transformation of profit per employee (Panel d), (logged) total output per employee (panel e) and the firm TFP measure (panel f). 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 clustered by state.

Source: ASI 2009-2019.

Table 1: Descriptive statistics

	(1)	(2)	(3)
	Mean	**SD**	**N**
Panel A: Female Employment			
Proportion of Female Workers	0.122	0.241	870153
Proportion of Female Mandays	0.120	0.239	761843
Panel B: Firm Size			
Firm Size (Workers)	40.511	236.194	964485
Firm Size (All Employees)	75.915	414.969	964485
Firm Size (Output, INR)	2.734e+08	5.523e+09	964485
Panel C: Other Firm Variables			
Welfare (INR, per employee)	2301.135	4646.865	954120
PF (INR, per employee)	3501.183	5406.843	954118
Gender Gap (female wage/male wage)	0.860	0.236	230141
Profit (INR, per employee)	90595.229	163399.333	901006
Labor Productivity (INR, output per employee)	1705573.934	3093527.424	954121
TFP	32670.788	1518429.368	891863

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 is defined as total workers in a firm. Firm Size (All Employees) refers to all employees including permanent 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. Gender wage gap is defined as the ratio of female wage rate by male wage rate. Labor productivity is defined as total value of real output per employee. Total factor Productivity (TFP) is measured using the method described in Levinsohn & Petrin (2003) and implemented using the procedure provided in Petrin *et al.* (2004) with average capital in a year to measure the capital stock in the current year. Provident Fund (PF) is annual social security contribution of the employer paid per employee. Welfare expenses refer to group benefits like direct expenditure on maternity, creches, canteen facilities, educational, cultural and recreational facilities, paid per employee annually. 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.
Source: Annual Survey of Industries (ASI) 1998-2019.

Table 2: 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)	0.028***	0.027***	0.027***	0.026***	0.045***	0.043***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ln(Firm Size)^2					-0.003***	-0.003***
					(0.000)	(0.000)
Mean Female Proportion	.121	.119	.121	.12	.121	.12
R-Squared	.851	.857	.855	.861	.855	.861
Observations	784652	681936	784521	681817	784521	681817
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Indus. × Yr FE			Yes	Yes	Yes	Yes
State × Yr FE			Yes	Yes	Yes	Yes
Panel B: Cross-Sectional Estimates						
ln(Firm Size)	0.048***	0.047***	0.028***	0.027***	0.041***	0.038***
	(0.007)	(0.007)	(0.003)	(0.002)	(0.006)	(0.005)
ln(Firm Size)^2					-0.002**	-0.002*
					(0.001)	(0.001)
Mean Female Proportion	.122	.121	.122	.121	.122	.121
R-Squared	.0853	.0837	.385	.387	.385	.388
Observations	836317	731955	836214	731860	836214	731860
Indus. × Yr FE			Yes	Yes	Yes	Yes
State × 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 3: Firm Size and Relative Female Employment (Individual Data)

	All workers		Full time	
	(1)	(2)	(3)	(4)
6- 9	-0.004	-0.002	0.001	0.002
	(0.003)	(0.004)	(0.004)	(0.004)
10-20	0.014**	0.019***	0.017**	0.023***
	(0.004)	(0.004)	(0.005)	(0.005)
20 and above	0.032***	0.041***	0.042***	0.051***
	(0.005)	(0.005)	(0.006)	(0.006)
Constant	0.182***	0.180***	0.165***	0.163***
	(0.002)	(0.002)	(0.002)	(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 4: Effect of Amendments on Relative Female Employment and Firm Size (DID Estimates)

	(1)	(2)	(3)	(4)	(5)
	Female Proportion		ln(Firm Size)		
	Workers	Workers	Workers	Employees	Output
Amendment	0.009*	0.008**	0.026	0.036	0.229*
	(0.005)	(0.004)	(0.040)	(0.028)	(0.112)
Mean of Female Proportion	.126	.126			
R-Squared	.868	.87	.824	.885	.577
Observations	296871	296871	296871	296871	296871
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Indus. × Yr FE	No	Yes	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 workers in column 3, log total employees (workers, supervisors, other, contract) in column 4 and log total value of output in column 5. Treated states are Rajasthan and Jharkhand in 2014 and 2017, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are heteroscedasticity robust and clustered at the state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Annual Survey of Industries 2009-2019.

Table 5: Firm Size and Nature of Labor Contracts and Benefits (Individual Data)

Dependent Variable:	Part -time	Written Contract	Healthcare /Maternity	Pension	Paid Leave
	(1)	(2)	(3)	(4)	(5)
6- 9	-0.003	0.021***	0.016***	0.028***	0.030***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
10-20	0.001	0.049***	0.047***	0.078***	0.069***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
20 and above	-0.001	0.140***	0.151***	0.221***	0.161***
	(0.004)	(0.007)	(0.008)	(0.008)	(0.007)
Constant	0.038***	0.153***	0.120***	0.178***	0.228***
	(0.002)	(0.002)	(0.003)	(0.003)	(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: NSS rounds 55, 61, 66 and 68, PLFS 2017-18 and PLFS 2018-19. Column 1 contain data from NSS rounds 55, 61, 66 and 68. Columns 2, 3 and 5 contain data from NSS rounds 61, 66 and 68. Columns 2-5 additionally contain data from PLFS 2017-18 and PLFS 2018-19. This is because NSS round 55 does not contain details on paid leave, written contract, healthcare/ maternity or pension; It only has data on whether the respondent was covered under any type of provident fund. PLFS does not contain details on part/full time work.

Table 6: Effect of Amendments on Other Firm Outcomes (DID Estimates)

	(1) Welfare per employee	(2) PF per employee	(3) Gender Gap	(4) Profit per employee	(5) Labor Productivity	(6) TFP
Amendment	0.234***	0.057	-0.022**	0.357***	0.113	0.028*
	(0.050)	(0.072)	(0.011)	(0.116)	(0.083)	(0.015)
R-Squared	.743	.805	.457	.479	.687	.754
Observations	296870	296866	89074	272402	292502	273466
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Indus. × Yr FE	Yes	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, log female to male wage rate, IHS transformation of profits per employee, log labor productivity (output per employee), and log TFP in columns 1, 2, 3, 4 , 5 and 6 respectively. Treated states are Rajasthan and Jharkhand in 2014 and 2017, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are heteroscedasticity robust and clustered at the state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Annual Survey of Industries 2009-2019.

Table 7: Firm Size and Gender Wage Gap (Individual Data)

	(1)	(2)	(3)	(4)
		ln(wage)		
6- 10	0.090***	0.083***	0.076***	0.072***
	(0.006)	(0.006)	(0.006)	(0.006)
10-20	0.145***	0.133***	0.136***	0.130***
	(0.007)	(0.007)	(0.007)	(0.006)
20 and above	0.282***	0.259***	0.266***	0.248***
	(0.009)	(0.008)	(0.007)	(0.007)
Female			-0.451***	-0.428***
			(0.012)	(0.012)
Female × 6-10			0.081***	0.064***
			(0.016)	(0.017)
Female × 10-20			0.076***	0.054**
			(0.018)	(0.019)
Female × 20 and above			0.131***	0.116***
			(0.022)	(0.020)
Constant	5.615***	5.618***	5.694***	5.692***
	(0.003)	(0.003)	(0.003)	(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

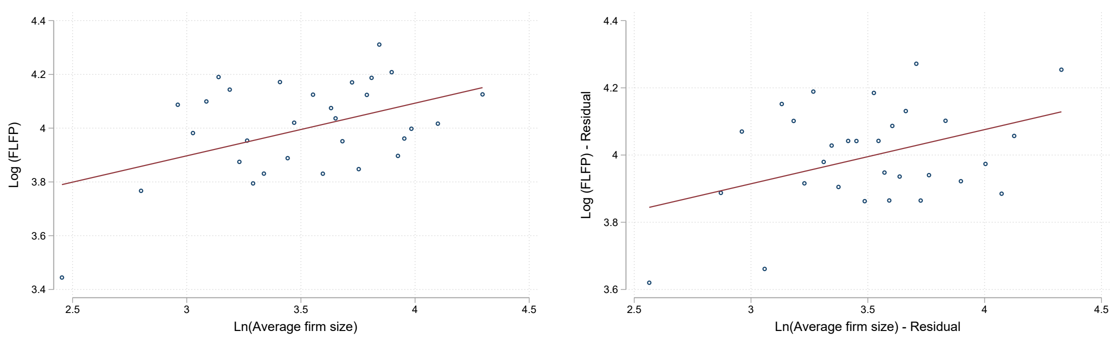
Notes: The dependent variable is log of real daily wage (at 2017 prices) for all columns. Controls include age, age square, education level, religion, social group, sector (rural/urban) and marital status. Mean of DV denotes the mean of the dependent variable without log transformation. The sample includes 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.

ONLINE APPENDIX

A Appendix: Figures and Tables

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

(a) No controls (b) Accounting for Income Per Capita

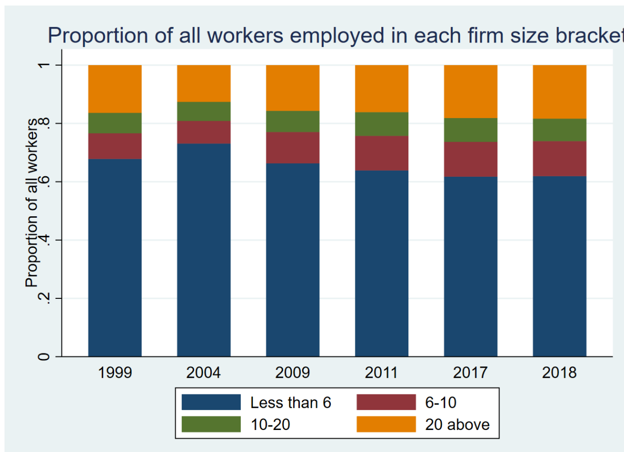


Notes: Panel (a) plots the binscatter of log of female labor force participation (FLFP) vs. the log of average firm size in the formal sector across countries. Panel (b) plots the binscatter of log of FLFP vs. the log of average firm size in the formal sector across countries, after controlling for the 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)

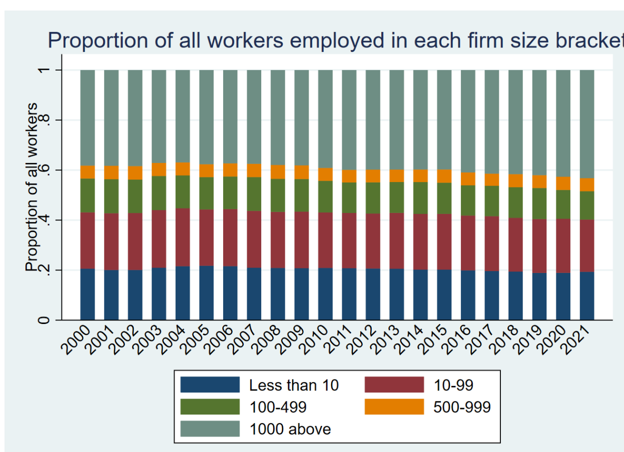
Source: OECD report for firm size data for the OECD countries for year 2014 or the latest year of availability. This is based on enterprise data collected by individual countries. For other countries we use the World Bank Enterprise Data (WBED) for firm size (average between 2006-2019). WBED is collected 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: Firm size distribution: India vs US

(a) India: NSS



(b) USA: CPS

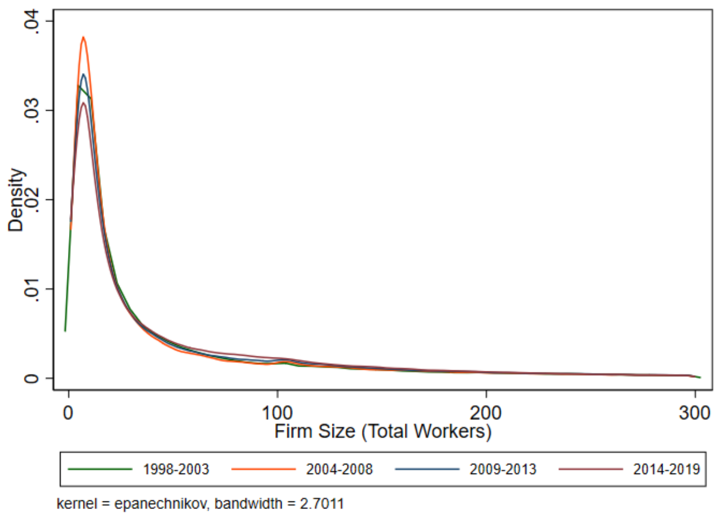


Notes: Panels (a) and (b) plot proportion of workers in each firm size category for India and the US, respectively.

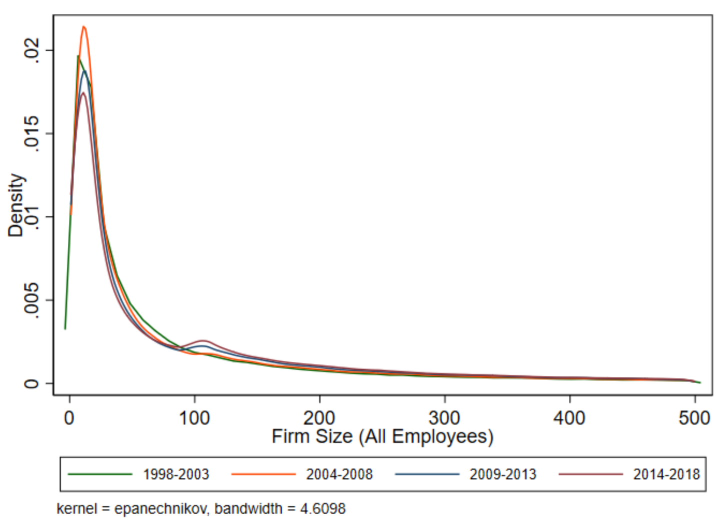
Source: NSS and PLFS (India) and CPS (US), various rounds.

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

(a) Total Workers

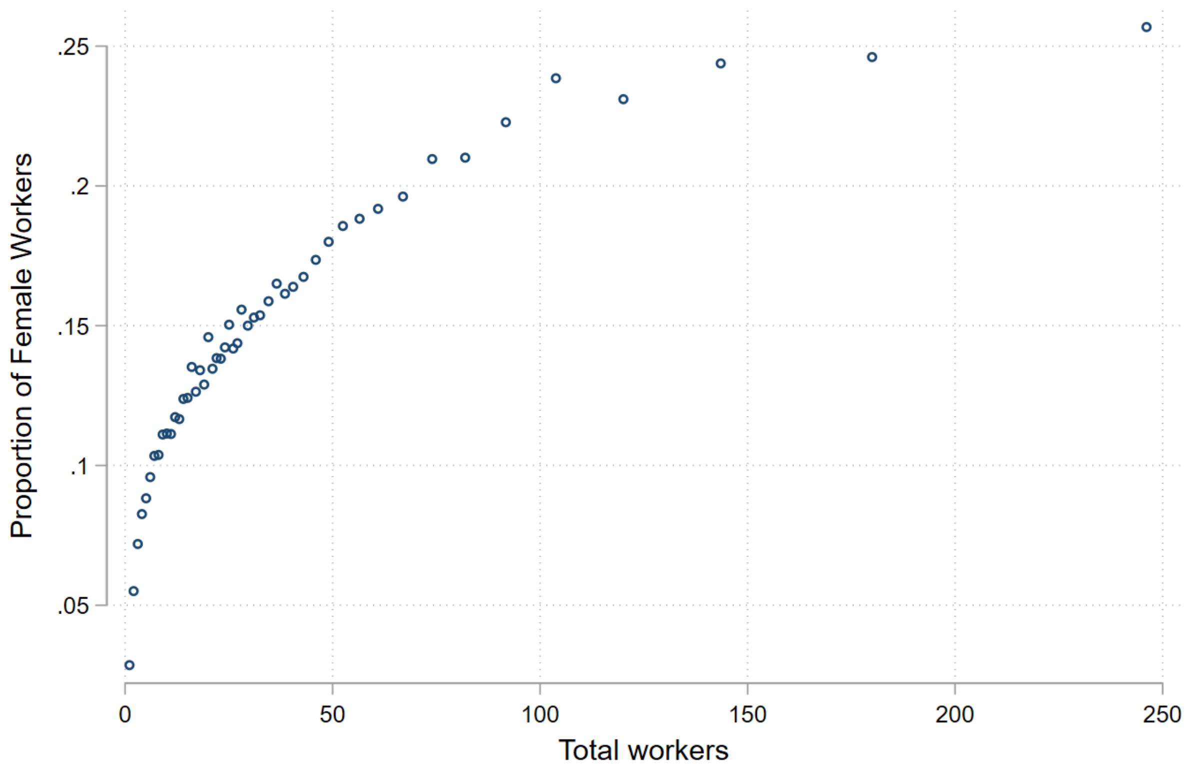


(b) Total Employees



Notes: Panel (a) plots the density of firm size distribution for total workers. Panel (b) plots the density of the distribution for total employees (workers+supervisors+other+contract workers).
Source: ASI 1998-2019.

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

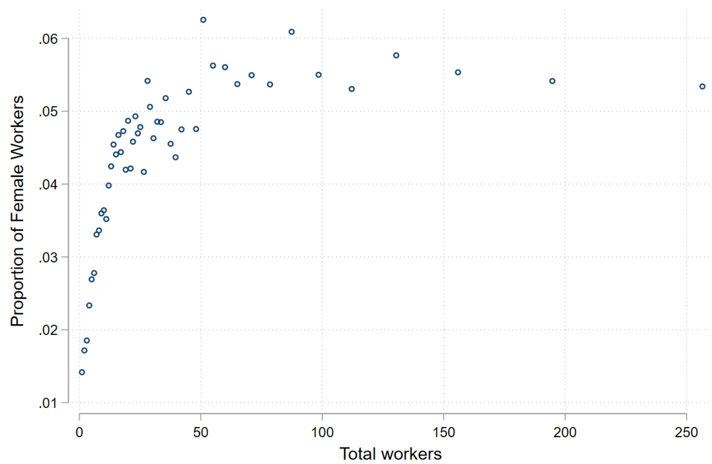


Notes: The figure plots the binscatter between the proportion of female workers and total workers in a firm after excluding public sector enterprises enterprises.

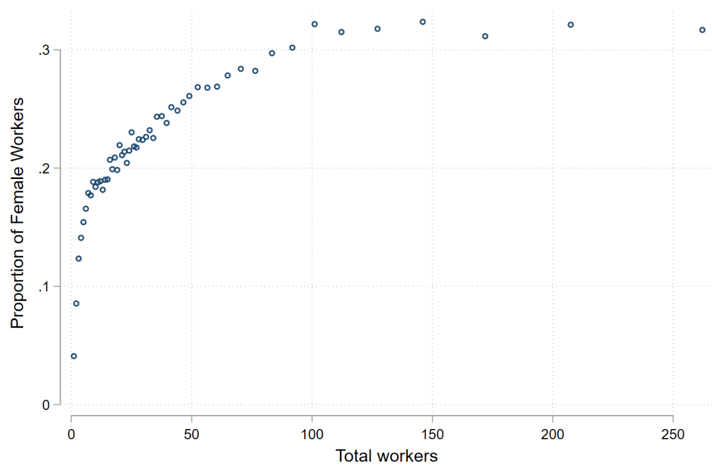
Source: ASI 1998-2019.

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

(a) Northern India



(b) Southern India



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: ASI 1998-2019.

Table A.1: Firm Size and Relative Female Employment (ASI data): Robustness to Alternative Definitions and Controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Female Proportion					
	Worker	Mandays	Worker	Mandays	Worker	Mandays
ln(Firm Size (All Employees))	0.022***	0.022***				
	(0.001)	(0.001)				
ln(Firm Size (Output))			0.005***	0.006***		
			(0.000)	(0.001)		
ln(Firm Size)					0.025***	0.025***
					(0.001)	(0.001)
Export Share					0.003*	0.004*
					(0.002)	(0.002)
Mean Female Proportion	.121	.119	.121	.119	.12	.12
R-Squared	.853	.859	.852	.858	.876	.877
Observations	784521	681939	784521	682036	461775	461548
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Indus. × Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Yr FE	Yes	Yes	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 1-2. In columns 3-4, firm size (Output) is defined as log of total real value of output. In columns 5-6, firm size is defined as log of total workers. 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.2: Firm Size and Relative Female Employment across Sectors (ASI Data)

	(1)	(2)	(3)	(4)
Sectors:	Rural		Urban	
	Worker	Mandays	Worker	Mandays
Panel A: Panel Estimates				
ln(Firm Size)	0.031***	0.030***	0.024***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)
Mean Female Proportion	.15	.145	.102	.101
R-Squared	.875	.882	.852	.856
Observations	306652	269414	451886	390041
Firm FE	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)	0.032***	0.031***	0.024***	0.023***
	(0.004)	(0.003)	(0.002)	(0.002)
Mean Female Proportion	.149	.144	.106	.105
R-Squared	.446	.452	.352	.352
Observations	338237	298823	497846	432924
Indus. $\times$ Yr FE	Yes	Yes	Yes	Yes
State $\times$ Yr FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: The dependent variable is proportion of female workers in column 1 and column 3, and proportion female worker mandays in column 2 and column 4. Columns 1-2 report the effects for rural regions and columns 3-4 report the effects for urban regions. 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 A.3: Firm Size Categories and Relative Female Employment (ASI Data)

	(1)	(2)	(3)	(4)
	Worker	Mandays	Worker	Mandays
5-10	0.034***	0.032***	0.034***	0.033***
	(0.001)	(0.001)	(0.001)	(0.001)
10-25	0.052***	0.049***	0.051***	0.049***
	(0.002)	(0.002)	(0.001)	(0.002)
25-50	0.068***	0.065***	0.066***	0.064***
	(0.002)	(0.002)	(0.002)	(0.002)
50-100	0.080***	0.076***	0.077***	0.074***
	(0.002)	(0.002)	(0.002)	(0.002)
100-300	0.093***	0.089***	0.089***	0.086***
	(0.002)	(0.002)	(0.002)	(0.002)
>= 300	0.113***	0.109***	0.106***	0.103***
	(0.003)	(0.003)	(0.003)	(0.003)
Mean Female Proportion	.121	.119	.121	.119
R-Squared	.850215	.8564654	.8540655	.8598394
Observations	784652	682155	784521	682036
Firm FE	Yes	Yes	Yes	Yes
Indus. × Yr FE	No	No	Yes	Yes
State × 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 female and male workers. 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***	0.055***	0.092***	0.158***		
	(0.002)	(0.002)	(0.002)	(0.004)		
log (Firm Size)^2				-0.035***		
				(0.001)		
log (Firm Size (Hired))					0.028***	0.025***
					(0.001)	(0.002)
log (Firm Size (Hired))^2						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 × Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × 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 workers among total workers (including unpaid employees) in columns 1-4. The dependent variable is defined as the proportion of hired female workers among all hired workers 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***	0.030***	0.072***	0.051***
	(0.007)	(0.003)	(0.004)	(0.002)
10-25	0.082***	0.071***	0.108***	0.091***
	(0.008)	(0.004)	(0.005)	(0.004)
25-50	0.094***	0.093***	0.118***	0.105***
	(0.012)	(0.007)	(0.011)	(0.005)
50-100	0.080***	0.111***	0.126***	0.106***
	(0.016)	(0.011)	(0.029)	(0.010)
100-300	0.048	0.091***	0.231**	0.100***
	(0.034)	(0.008)	(0.107)	(0.014)
>= 300	0.390***	0.094***	0.163***	0.225***
	(0.041)	(0.013)	(0.047)	(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**	0.038***	0.081***	0.043***
	(0.008)	(0.005)	(0.004)	(0.003)
10-25	0.083***	0.082***	0.114***	0.074***
	(0.010)	(0.006)	(0.006)	(0.005)
25-50	0.088***	0.128***	0.130***	0.096***
	(0.013)	(0.011)	(0.011)	(0.010)
50-100	0.070***	0.149***	0.100***	0.103***
	(0.018)	(0.018)	(0.015)	(0.022)
100-300	0.059*	0.107***	0.067***	0.092***
	(0.033)	(0.012)	(0.020)	(0.016)
>= 300	0.405***	0.098***	0.130**	0.235***
	(0.042)	(0.018)	(0.058)	(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**	0.027***	0.066***	0.051***
	(0.008)	(0.003)	(0.004)	(0.002)
10-25	0.048*	0.064***	0.103***	0.091***
	(0.027)	(0.004)	(0.008)	(0.004)
25-50	0.139***	0.070***	0.107***	0.099***
	(0.020)	(0.006)	(0.017)	(0.006)
50-100	0.166***	0.077***	0.142***	0.098***
	(0.029)	(0.008)	(0.045)	(0.009)
100-300	-0.085	0.080***	0.343***	0.098***
	(0.103)	(0.009)	(0.129)	(0.018)
>= 300	0.233***	0.091***	0.200***	0.218***
	(0.062)	(0.017)	(0.064)	(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 Ownership Gender

	(1)	(2)	(3)	(4)
	Agriculture	Manufacturing	Construction	Services
	Panel A: Male Owned Firms			
Firm Size (Hired)				
5-10	0.022***	0.040***	0.077***	0.062***
	(0.007)	(0.003)	(0.003)	(0.002)
10-25	0.089***	0.081***	0.112***	0.106***
	(0.009)	(0.005)	(0.005)	(0.004)
25-50	0.103***	0.103***	0.125***	0.125***
	(0.012)	(0.008)	(0.011)	(0.005)
50-100	0.080***	0.124***	0.133***	0.123***
	(0.017)	(0.012)	(0.029)	(0.011)
100-300	0.039	0.102***	0.252**	0.115***
	(0.031)	(0.009)	(0.107)	(0.015)
>= 300	0.407***	0.112***	0.209***	0.243***
	(0.045)	(0.013)	(0.058)	(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***	-0.145***	-0.060***	-0.117***
	(0.015)	(0.012)	(0.016)	(0.007)
10-25	-0.002	-0.094***	-0.036	-0.078***
	(0.036)	(0.013)	(0.027)	(0.008)
25-50	-0.044	-0.088***	-0.066**	-0.097***
	(0.029)	(0.013)	(0.028)	(0.009)
50-100	0.092**	-0.088***	-0.023	-0.089***
	(0.044)	(0.020)	(0.067)	(0.013)
100-300	0.099	-0.083***	-0.016	-0.073***
	(0.113)	(0.018)	(0.060)	(0.016)
>= 300	0.295***	-0.084***	-0.104	0.063
	(0.052)	(0.029)	(0.069)	(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**
Panel A: Outcome Variables			
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
Panel B: Firm Size Variable			
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.

Table A.9: Effect of Amendments on Relative Female Employment and Firm Size (DID Estimates): Robustness to Alternative Definitions

	Any female	ln(Female workers)	ln(Male workers)	Female proportion	
	(1)	(2)	(3)	(4)	(5)
	Workers	Workers	Workers	Mandays	Workers
Amendment	0.034*	0.162*	0.004	0.009**	0.009**
	(0.016)	(0.083)	(0.033)	(0.004)	(0.004)
Amendment × Rural					-0.000
					(0.001)
Mean	.333	29	88.5	.134	.134
R-Squared	.783	.854	.824	.869	.87
Observations	296871	296871	296871	296871	296871
Firm FE	Yes	Yes	Yes	Yes	Yes
Indus. × Yr FE	Yes	Yes	Yes	Yes	Yes

Notes: The table reports difference-in-differences estimation results for the outcome variables of firm size and female employment (two way fixed effects). 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 and proportion of female workers in column 5. Treated states are Rajasthan and Jharkhand in 2014 and 2017, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are heteroscedasticity robust and clustered at the state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Annual Survey of Industries 2009-2019.

Table A.10: Effect of Amendments on Relative Female Employment and Firm Size (DID Estimates) : Robustness to Alternative Specifications

	(1)	(2)	(3)	(4)
	Female Proportion	ln(Firm Size)		
	Workers	Workers	Employees	Output
	Panel A: Weighted			
Amendment	0.008*	0.070	0.051	0.345*
	(0.004)	(0.049)	(0.039)	(0.195)
Mean of Female Proportion	.126			
R-Squared	.862	.823	.872	.677
Observations	296871	296871	296871	296871
	Panel B: 2001-2019			
Amendment	0.007**	0.012	0.040	0.262**
	(0.003)	(0.063)	(0.036)	(0.122)
Mean of Female Proportion	.128			
R-Squared	.858	.792	.86	.528
Observations	494277	494277	494277	494277
	Panel C: All States			
Amendment	0.004*	0.059**	0.054**	0.187**
	(0.002)	(0.027)	(0.025)	(0.082)
Mean of Female Proportion	.106			
R-Squared	.858	.824	.895	.573
Observations	462298	462298	462298	462298
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Indus. × Yr FE	Yes	Yes	Yes	Yes

Notes: The table reports difference-in-differences estimation results for the outcome variables of proportion of female workers and firm size. The dependent variable is proportion of female workers in column 1, log total workers in column 2, log total employees in column 3 and log total value of output in column 4. Treated states are Rajasthan and Jharkhand in 2014 and 2017, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions weighted by sampling weights in panel A, all years included from 2001 in panel B and all states included who undertook amendments of the Factories Act or the Industrial Disputes Act irrespective of whether night shift amendments for allowing female employees were made. Standard errors in brackets are heteroscedasticity robust and clustered at the state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Annual Survey of Industries 2009-2019.

Table A.11: Effect of Amendments on Relative Female Employment and Firm Size: Robustness (PSM-DID)

	(1)	(2)	(3)	(4)
	Female Proportion	ln(Firm Size)		
	Workers	Workers	Employees	Output
Amendment	0.008***	0.091	0.028	0.358***
	(0.003)	(0.054)	(0.029)	(0.121)
Mean of Female Proportion	.0497			
R-Squared	.804	.837	.876	.573
Observations	37313	37313	37313	37313
F-Stat	0.11	0.11	0.11	0.11
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Indus. × Yr FE	Yes	Yes	Yes	Yes

Notes: The table reports matched difference-in-differences estimation results for the outcome variables of proportion of female workers and firm size. The dependent variable is proportion of female workers in column 1, log total workers in column 2, log total employees in column 3 and log total value of output in column 4. Treated states are Rajasthan and Jharkhand in 2014 and 2017, respectively. We match the firms in the treated states with firms in the control states using a propensity-score reweighting approach (nearest neighbor matching with caliper of 0.1) and then conduct then estimate the difference-in-differences effect using the weights obtained. The covariates using for matching include the three-digit industry codes, organization type (private limited, public limited, individual proprietorship, partnership etc), quartiles for plant age (less than 5 years, 5-10 years, 10-25 years, more than 25 years) and sector (rural/urban). Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are heteroscedasticity robust and clustered at the state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Annual Survey of Industries 2009-2019.

Table A.12: Nature of Labour Contract-Benefits and Relative Female Employment (Individual data)

	(1)	(2)	(3)	(4)
Part Time	0.187***	0.171***		
	(0.013)	(0.013)		
Written	0.022***	0.027***	0.017***	0.020***
	(0.007)	(0.007)	(0.005)	(0.005)
Healthcare/	0.019***	0.020***	0.018***	0.019***
Maternity	(0.006)	(0.006)	(0.005)	(0.005)
Pension/PF/Gratuity	-0.052***	-0.059***	-0.050***	-0.053***
	(0.008)	(0.008)	(0.007)	(0.008)
Paid Leave	-0.009*	-0.004	-0.011**	-0.006
	(0.005)	(0.005)	(0.004)	(0.004)
Constant	0.195***	0.195***	0.205***	0.204***
	(0.002)	(0.002)	(0.002)	(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 55, 61, 66 and 68. PLFS 2017-18 and PLFS 2018-19 are excluded from the analyses in columns 1 and 2 because the PLFS does not contain details on part/full time work.

Table A.13: 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*	0.003	0.118***	0.101***	0.081***	0.060***	0.052***	0.136***
	(0.017)	(0.016)	(0.014)	(0.013)	(0.014)	(0.016)	(0.017)	(0.016)
51-200	0.067***	0.169***	0.346***	0.248***	0.247***	0.278***	0.214***	0.269***
	(0.017)	(0.015)	(0.014)	(0.012)	(0.014)	(0.016)	(0.017)	(0.015)
201-500	0.268***	0.334***	0.462***	0.332***	0.355***	0.445***	0.383***	0.380***
	(0.017)	(0.016)	(0.015)	(0.013)	(0.014)	(0.017)	(0.017)	(0.016)
501-1000	0.413***	0.402***	0.493***	0.346***	0.385***	0.489***	0.455***	0.422***
	(0.018)	(0.017)	(0.015)	(0.014)	(0.015)	(0.018)	(0.018)	(0.017)
1001-5000	0.527***	0.449***	0.508***	0.361***	0.405***	0.542***	0.505***	0.458***
	(0.018)	(0.017)	(0.015)	(0.014)	(0.015)	(0.017)	(0.018)	(0.017)
5001-10000	0.570***	0.447***	0.501***	0.347***	0.401***	0.532***	0.498***	0.466***
	(0.026)	(0.024)	(0.022)	(0.019)	(0.021)	(0.025)	(0.026)	(0.024)
10001 - 50000	0.562***	0.454***	0.508***	0.356***	0.402***	0.525***	0.515***	0.471***
	(0.025)	(0.024)	(0.022)	(0.019)	(0.021)	(0.024)	(0.025)	(0.023)
50001 - 100000	0.471***	0.402***	0.471***	0.317***	0.387***	0.511***	0.363***	0.436***
	(0.048)	(0.045)	(0.041)	(0.036)	(0.040)	(0.047)	(0.048)	(0.044)
100001+	0.400***	0.389***	0.446***	0.329***	0.350***	0.399***	0.400***	0.433***
	(0.039)	(0.037)	(0.033)	(0.029)	(0.033)	(0.038)	(0.039)	(0.036)
Constant	0.273***	0.442***	0.438***	0.610***	0.557***	0.383***	0.398***	0.480***
	(0.016)	(0.015)	(0.014)	(0.012)	(0.013)	(0.015)	(0.016)	(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 headquater 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.14: Firm Size (total employees) and Other Firm Outcomes (ASI data)

	(1)	(2)	(3)	(4)	(5)	(6)
	Welfare per capita	PF per capita	Gender Wage Gap	Profit per capita	Labor Productivity	TFP
			Panel A: Panel Estimates			
ln(Firm Size)	0.425***	0.381***	0.001	1.033***	0.589***	0.052***
	(0.008)	(0.009)	(0.002)	(0.028)	(0.012)	(0.003)
R-Squared	.765	.823	.543	.504	.714	.774
Observations	864987	864985	192570	812512	864988	804664
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Indus. × Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
			Panel B: Cross-Sectional Estimates			
ln(Firm Size)	0.693***	0.784***	0.002	0.822***	0.448***	0.248***
	(0.020)	(0.020)	(0.002)	(0.041)	(0.029)	(0.006)
R-Squared	.388	.385	.0927	.0697	.257	.411
Observations	915211	915209	221948	866096	915212	858003
Indus. × Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	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 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.15: Firm Size (output) and Other Firm Outcomes (ASI data)

	(1)	(2)	(3)	(4)	(5)	(6)
	Welfare per capita	PF per capita	Gender Wage Gap	Profit per capita	Labor Productivity	TFP
			Panel A: Panel Estimates			
ln(Firm Size)	0.249***	0.233***	-0.000	1.394***	0.854***	0.533***
	(0.003)	(0.004)	(0.002)	(0.009)	(0.001)	(0.004)
R-Squared	.769	.826	.543	.534	.953	.801
Observations	864987	864985	192592	812512	864988	804664
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Indus. × Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
			Panel B: Cross-Sectional Estimates			
ln(Firm Size)	0.324***	0.377***	0.008**	1.344***	0.860***	0.479***
	(0.014)	(0.013)	(0.003)	(0.026)	(0.005)	(0.012)
R-Squared	.373	.37	.0931	.149	.828	.475
Observations	915211	915209	221971	866096	915212	858003
Indus. × Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	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 1. Firm size is defined as total real output produced by a firm. Controls used 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.16: Effect of Amendments on Number of Firms (DID Estimates)

	(1)	(2)	(3)	(4)
	number of firms		ln(number of firms)	
Amendment	0.803	1.281	0.047	0.085
	(2.371)	(2.425)	(0.087)	(0.093)
Mean of number of firms	23.9	24	23.9	24
R-Squared	.14	.386	.195	.679
Observations	14298	14215	14298	14215
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Indus. × 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 and Jharkhand in 2014 and 2017, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are heteroscedasticity robust and clustered at the state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Annual Survey of Industries 2009-2019.

B Model: Extension

Here we discuss an alternative version of the model with a *continuum of amenities*, where $a \in [\underline{a}, \bar{a}]$ 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:

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

where

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

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:

$$N_m : \qquad \frac{\partial Y}{\partial N_m} = w_m \tag{B.2}$$

$$N_f : \qquad \frac{\partial Y}{\partial N_f} = w_f \tag{B.3}$$

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

Substituting the functional forms yields the following:

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

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

$$\begin{aligned} a : \qquad & z \left\{ (z_m(a) N_m)^{\frac{\sigma-1}{\sigma}} + \tau(z) \left(z_f(a) N_f \right)^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{1}{\sigma-1}} \\ & \left\{ (z_m N_m)^{-\frac{1}{\sigma}} N_m z_m'(a) + \tau(z) \left(z_f N_f \right)^{-\frac{1}{\sigma}} N_f z_f'(a) \right\} = C'(a) \end{aligned} \tag{B.7}$$

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:

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

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,

$$\begin{aligned}
\frac{\tau(z)\left(z_f N_f\right)^{-\frac{1}{\sigma}} z_f(a)}{\left(z_m N_m\right)^{-\frac{1}{\sigma}} z_m(a)} &= \left\{\frac{N_f}{N_m}\frac{k_m}{k_f a^\rho}\right\}^{\frac{1}{\epsilon}} \\
\implies \frac{N_f}{N_m} &= \left\{\tau(z) a^{\frac{\rho}{\epsilon}}\left(\frac{z_f(a)}{z_m(a)}\right)^{1-\frac{1}{\sigma}}\left(\frac{k_f}{k_m}\right)^{\frac{1}{\epsilon}}\right\}^{\frac{\sigma\epsilon}{\sigma+\epsilon}} && \text{(B.8)} \\
\frac{w_f}{w_m} &= \left\{\left\{\tau(z) a^{\frac{\rho}{\epsilon}}\left(\frac{z_f(a)}{z_m(a)}\right)^{1-\frac{1}{\sigma}}\left(\frac{k_f}{k_m}\right)^{\frac{1}{\epsilon}}\right\}^{\frac{\sigma\epsilon}{\sigma+\epsilon}}\frac{k_m}{k_f a^\rho}\right\}^{\frac{1}{\epsilon}} && \text{(B.9)}
\end{aligned}$$

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 (τ) remains unchanged, the ratio of female to male workers will increase if the female average productivity response to amenities is higher than men. If τ increases with firm size, there is a further shift towards female employees. If τ 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:

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

where $Y \in$ {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 $ln(Firm\ Size) \in$ {log of total workers, log of total employees, log of total output} in a firm.[1] δ_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, δ_{jt} are the industry (4 digit) times year fixed effects which control for industry-specific changes over time, and δ_{st} are the state times year fixed effects. The main coefficient of interest is γ_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 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

[1]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 & 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.

cross-sectional estimates.[2]

C.2 Individual data

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

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

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 square, education, religion, caste, marital status, and rural-urban location of the household. As previously, we control for unobservables that can affect proportion of female workers across industries and location – δ_{dt} and δ_{nt} refer to district by year, and industry by year fixed effects, respectively.[3] Additionally, the individual level data also record the occupation of work. Hence, we control for δ_{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 firm 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 then the positive relationship should no longer 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

[2]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 very intensive and do not converge in our case. Additionally, Papke & 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.

[3]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, α_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 the 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, experience, and be similar in every aspect except the gender. These profiles were used to systematically applied 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 CV's. 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 an educational qualifications of a BA (Bachelor of Arts) and an MBA (Masters in Business Administration) in HRM (Human Resource Management). The finance profiles have 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 profiles were different they were selected to be similar in term of quality and ranking so that it gave similar signal about ability of candidates.

Both male and female profiles for a given role had similar age 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, 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 is prominently displayed on their CVs. The first and last names were selected to avoid signaling any sociol-economic differences, with all profiles indicating upper-caste Hindu backgrounds.

D.2 Selection of Jobs

We developed an algorithm that scraped the 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 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 for a 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, eg 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 roaster of relevant and active job openings within each sector twice in 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 were 5238 (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%, compared to 3.8% 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.[1] Notably, female profiles with similar skills are less likely to receive a callback from larger receive compared to comparable male profiles (1 pp 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.

$$CB_{i,j} = \beta \; Female_i + \gamma_j + \epsilon_{i,j} \tag{D.1}$$

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 Female$_i$, which equals 1 if the profile i is female, and 0 if male. γ_j represents job fixed effects, accounting for characteristics specific to each job that might influence callback rates. β 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

[1] In terms of posted wages, the average wages across the three firm size categories 1-50, 51-200 and more than 200 were 5 lakhs, 4.9 lakhs, and 5.6 lakhs 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.

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

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

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 CallbackRate = Total positive callbacks/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***	0.000	-0.008*	0.001	-0.014***
	(0.002)	(0.013)	(0.004)	(0.003)	(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	0.111**	-0.000	0.009	-0.004
	(0.010)	(0.047)	(0.016)	(0.015)	(0.016)
Female $\times$ Fsize$= [51 - 200]$	-0.022**	-0.111*	-0.020	-0.005	-0.012
	(0.011)	(0.058)	(0.019)	(0.016)	(0.017)
Female $\times$ Fsize> 200	-0.020*	-0.130***	-0.004	-0.010	-0.010
	(0.010)	(0.049)	(0.016)	(0.015)	(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**	0.000	-0.020*	0.004	-0.016**
	(0.005)	(0.034)	(0.010)	(0.007)	(0.007)
(Female) + (Female $\times$ Fsize> 200)	-0.010***	-0.018	-0.004	-0.002	-0.014***
	(0.003)	(0.014)	(0.004)	(0.002)	(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 51â200 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.