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

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Abstract

Using firm and individual-level data, we show 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 and also improved overall environment for firm growth. We document a resulting 5 percent increase in female worker share in the treated states, along with a 4 percent and 13 percent 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 industrial policies promoting firm growth can enhance female employment.

JEL Codes: J20, J16, L25, L50

Keywords: Employment, gender, firm size, labor laws, amenities

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1 Introduction

Female labor force participation (FLFP) rate varies from 52 percent in the OECD countries to 22 percent 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 income effect (Panel (b)).[1] If job attributes systematically differ such that jobs in bigger firms are more attractive for women vs. men, then the firm-size distribution may be a limiting factor for female employment in a country. Theoretically, bigger firms, which are more productive, can find it profitable to provide non-wage amenities valued relatively more by women, like creches, maternity benefits, transport, etc., and attract more women into the workforce. This paper investigates the relationship between firm size and female employment and whether policies that spur firm growth can also increase female employment. We examine this question in the context of India, characterized by low FLFP rates of around 27 percent (ILO estimates) and a country dominated by small firms – almost 75 percent of the non-farm workforce in India is employed in firms having less than 10 employees (Figure A.2).[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 and firm size (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 of 0.2 between

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

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

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 capture individual employment details. We find that the reduced form positive relationship persists between firm size and female employment, even after we control for individual characteristics and variation across district-year and industry-occupation-year levels.

Next, we use exogenous variation in labor law amendments across states of India to verify whether policies that can potentially spur firm growth can also increase female employment. These amendments were enacted by five states in the country—Rajasthan (2014), Jharkhand (2017), Maharashtra (2016), Madhya Pradesh (2015) and Uttar Pradesh (2018)—combined having more than 500 million people, thus exceeding countries like the US in terms of population. 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 retrench workers and close an establishment without prior government permission from 100 to 300 workers. Further, in some states, violations under these acts by the employer were decriminalized and Contract Labor Act was also amended to apply to firms having 50 contract workers, from the earlier limit of 20. These amendments provided a direct incentive for firms to grow beyond the thresholds of 20, 40, and 100 and eased the compliance costs for other firms by decriminalizing non-compliance. It also provided establishments that employed between 100 and 300 permanent workers flexibility in 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 establishment chooses to spend on.

We estimate the causal impact of the amendments on female workforce share, firm size, and related outcomes using a differences-in-differences framework. An event study design confirms no differential pre-treatment trends across treated and control states. In a two-way fixed effects specification, the amendments raise the proportion of female workers by 4 percent in treated states, accompanied by increases in the number of female workers, female mandays, and the likelihood that an establishment hires a woman. Applying recent methods for staggered adoption (Callaway & Sant'Anna, 2021) yields a 5 percent rise in female share. We also observe a 4 percent increase in employees and a 13 percent increase in output post amendments, indicating that growth enabling policies can boost female employment. Finally, using the Synthetic Difference-in-Differences (SDID) estimator Arkhangelsky *et al.* (2021), which constructs a weighted control to enforce parallel trends, we again find no pre-trends and detect a 3.5 percent increase in female share and a 6 percent rise in firm employment after the amendments.

Next, we examine the mechanisms through which larger firms can employ relatively more females. Using a theoretical framework, we show that following channels can potentially explain the positive relationship – (i) bigger firms provide higher non-wage amenities valued relatively more by women, (ii) bigger firms have different task requirements such that bigger firms have greater demand for female tasks, and (iii) lower discrimination against women – last two directly increase the demand for female labor. Using individual-level data, we confirm that workers employed in larger firms (20 or more workers) are 70 percent more likely to get maternity benefits, 45 percent more likely to get paid leaves, 50 percent more likely to have a written contract, and 70 percent 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 lead to increased expenditure on employee welfare by establishments. 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 by firm size, 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 gender disaggregated data only for workers involved in the process of manufacturing, among whom task variation with size is likely to be limited.[3] This shows that there exists an explanation beyond the differential task requirements across firm-size distribution.

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 25 percent less likely to receive a callback, bigger firms are either more likely or equally likely than smaller firms to give lower callbacks to similar female profiles. 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 differential or in fact smaller gender wage gap in bigger vs. smaller firms in our data.[4]

Taken together, the above findings indicate that bigger firms can employ more women due

[3]For instance, the existing literature showing that an increase in exports leads to greater employment of women generally finds increased demand for non-production tasks or interpersonal skills as the main channel (Bonfiglioli & De Pace, 2021; Banerjee *et al.*, 2022).

[4]It could also be that bigger firms have diversity targets and specifically look to hire women. However, this would lead to lower profits for bigger firms, and we do not find a fall in the profit per employee as firm size increases. 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 diversity initiatives by bigger firms are unlikely to be the main driver behind the obtained association.

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. 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 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 in bigger firms. In fact, individual-level data show that the gender gap in wages, if anything, is smaller in bigger 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.[5]

Our work contributes to several strands of literature. First, we contribute directly to the literature on firm-level determinants of female employment. Surprisingly, there has been little research in this area, with the most attention paid to the exporting status of a firm.[6] In a recent study, Chiplunkar & Goldberg (2024) show that female worker shares are higher in women-owned enterprises, and hence, removing barriers to female entrepreneurship can be an effective policy solution to increase female employment and aggregate economic productivity. However, other attributes, such as firm size, have not gained much attention in the literature. Mitra (2003) descriptively notes that women are more likely to be employed in larger establishments in their sample of 2240 US professional workers.[7] Thus, our study

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

[6]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 the 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.

[7]Card *et al.* (2016) show that sorting and bargaining effects across firms can explain 20 percent of the gender wage gap in Portugal, and when describing their sample descriptively note that females are more

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. Further, we examine 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. Existing literature for the developed countries shows that employer-provided welfare like child-care assistance (financial assistance for child-care, on-site child care), 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). Another strand of literature shows that women have equal or greater preference for non-pecuniary benefits (Goldin, 2014; Erosa *et al.*, 2022; Mas & Pallais, 2017; Wiswall & Zafar, 2018). In a recent study, Morchio & Moser (2024) explain the variation in the gender wage gap across firms through the provision of non-wage amenities by them. We extend and bring the two strands of literature together 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 (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 the 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 impact of amending labor regulations on overall employment and growth since these impose substantial costs on firms. Besley & Burgess (2004) show that amendments to the Industrial Disputes Act in India

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.

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.[8] In general, the literature studying the effect of policies on female employment mostly focuses on laws offering protection or benefits to women (maternity and parental leave, equal pay and anti-discriminatory laws, wage transparency laws), which in some cases have unintended consequences of reducing employer demand for them.[9] We extend this literature by showing that policies that are not protective of women can also spur employment for them.

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

2 Model

In this section, we develop a simple model of the labor market to discuss factors that can shape the relationship between firm size and female employment. We consider an economy with heterogeneous workers and a frictional labor market. The frictions that workers face in the labor market allow firms to enjoy market power. 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.[10]

[8] 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.

[9] 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.

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

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.[11] 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 $C > \bar{C}$[12].

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 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 following labor supply curves for men and women:

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

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

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

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 $k_f < k_m$. 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.

As discussed in detail in Section B in the Appendix, we first document that the more productive firms hire more workers. This is because 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, consistent with Lucas Jr (1978), and our empirical results documented in Section 5. For a given level of amenities, each worker would also receive higher wages, attracting more workers to the market. The equilibrium female-to-male labor ratio is given by:

$$\frac{N_f}{N_m} = \left\{ \tau(z) \left\{ z_f(a) \right\}^{\frac{\sigma-1}{\sigma}} a^{\frac{\rho}{\epsilon}} \left\{ \frac{k_f}{k_m} \right\}^{\frac{1}{\epsilon}} \right\}^{\frac{1}{\frac{1}{\sigma}+\frac{1}{\epsilon}}} \tag{3}$$

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 a higher degree of discrimination.

The equilibrium wage ratio is given by:

$$\frac{w_f}{w_m} = \left\{ \frac{k_m}{k_f a^\rho} \right\}^{\frac{1}{\sigma+\epsilon}} \left\{ \tau(z) \left\{ z_f(a) \right\}^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\frac{1}{\epsilon}}{\frac{1}{\sigma}+\frac{1}{\epsilon}}} \tag{4}$$

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 we show in Section B in the Appendix, if τ is non-decreasing or weakly decreasing with firm size, the difference in profits when firms provide higher versus lower amenities increases with their productivity and, therefore, with firm size. We document that 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.

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).[13] For the purpose of this paper, we use the terms *firm* and *establishment* interchangeably since multi-establishment firms constitute a very small proportion of all manufacturing enterprises in India.[14] The establishment-level ASI data is available from 1998-2019 and establishment identifiers are provided for the period between 1998 and 2019.[15]

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.[16] Gender-disaggregated employment data is captured only for manufacturing workers—including gender disaggregated mandays and wages for the manufacturing workers. Since manufacturing workers constitute 72 percent of all permanent

[13]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.

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

[15]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.

[16]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 employees.

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 capital expenditure. 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 A.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. The proportion of female mandays is similarly defined based on worker mandays. On average, women constitute 12 percent of total workers. Firm size based on employment is defined in terms of all paid employees (workers, supervisors, contract workers, and other employees). On average, a firm has 76 paid employees.[17] Alternatively, we also define firm size using the value of output (price $\times$ quantity) produced by a firm. This is deflated by a two-digit industry-specific Wholesale Price Index (WPI) with 2004 as the base year. The gender wage gap in a firm is defined as the ratio of the female daily wage rate to the male daily wage rate. The female (male) daily wage rate is computed by dividing wages paid to female (male) workers by female (male) worker mandays. On average, women receive 86 percent of the wage rate as men.

Figure 1 shows the scatter plot (binned) of the proportion of female workers across firm size. We see an increase in the proportion of female workers as firm size increases upto almost 120-130, and then it stays almost constant thereafter.[18] We next examine if this relationship

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

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

holds after controlling for other unobservable characteristics across firms.

3.1.1 Findings: Firm Level

We estimate the relationship between the proportion of female workers (or mandays) and firm size using two specifications (details in Appendix C). Table 1 reports the estimates for the proportion of female workers in columns (1), (3) and (5) and for 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 employees, by 1 percent is associated with a 0.024 and 0.023 increase in the proportion of female workers and mandays in a firm, respectively (columns 1-2). This translates into a 0.2 percent increase in the proportion of female workers when firm size increases by 1 percent. 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 one and half times 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 the proportion of female workers holds. Additionally, we find that the results persist even when alternative definitions of firm size are used—such as total output (Table A.2).

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.[19] We also estimate a specification where we divide 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.[20]

3.1.2 Alternate Firm-Level Data: Economic Census

We next examine whether the positive relationship between firm size and proportion of hired female employees (defined by female employees as a percentage of all employees). Columns (1)-(4) and (5)-(6) report the estimates for the proportion of women among all and hired employees

We undertake several other checks. Appendix Table A.5 shows that a higher proportion of women are employed by firms in bigger-size categories. 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 hired female employees by the gender of the firm's owner (notably, information about the owner's gender is not available in the ASI data). Around 8 percent 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 percent (Appendix Table A.7). Theoretically, as discussed in Section 2, lower discrimination, provision 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 in levels.[21]

[19] The estimates show that an increase in employees (output) by one percent increases the probability of females among the workers by 0.07 percentage points (0.017 percentage points). These results are omitted for brevity but available on request.

[20] We find an increase by 0.052 (43 percent 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 percent of mean) in the proportion of female workers in firms sized > 300 vs. those sized 1-5.

[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 percent are involved in

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). We find that 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 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 smaller for bigger firm size categories – giving rise to a U-shaped pattern between the proportion of women employees and firm size for female-owned enterprises.[22] Overall, however, the positive relationship dominates since 92 percent 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, 2024).

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 Labour Force Surveys (PLFS) conducted in 2017-18 and 2018-19 (referred to as 2017 and 2018 in the paper) for our analyses.[23] 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

manufacturing tobacco products, 10 percent in textiles, and 10 percent in the production of matchsticks. On the other hand, 4 percent, 14 percent, and less than 1 percent of male-owned enterprises are in these sectors, with no other sector exceeding 10 percent Thus, male-owned enterprises operate across a range of manufacturing products rather than specializing in a select few.

[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] 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. There is a small difference in

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 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 percent Around 60 percent 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 2 reports the estimation results for Equation C.2, where the dependent variable equals 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

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.

[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.

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 percent of mean) and 4.1 percentage points (or 22 percent 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 percent and 28 percent vs. firms with 1-5 workers, respectively (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 growth of the manufacturing sector in India. The key regulatory frameworks in India are anchored under the Factories Act, the Industrial Disputes Act and the Contract Labor Act.

The Factories Act and the regulations therein are applicable to manufacturing firms above certain employee size thresholds (historically 10 or more employees if using electric power and 20 otherwise). These regulations are mostly around worker health (cleanliness of the factory, proper disposal of waste, ventilation, temperature and lighting, number of workers per sq foot of space, toilets), worker safety (fire safety, 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 the number of female employees is more than 30.[27] Amirapu & Gechter (2020) estimate the increase in unit labor costs associated with these regulations to be around 35 percent when the firm size increases beyond 10 workers, thus creating a distortionary effect that incentivizes firms to remain small.

The Industrial Disputes Act (IDA) stipulates that any industrial establishment with more than a certain threshold of permanent employees must obtain prior permission from the state government before laying off workers or closing the establishment.[28] Existing evidence shows that the Factories Act, which increases the regulatory compliance costs, and the IDA, which reduces firm's flexibility to retrench workers during a negative shock contribute significantly to the small size of firms in India (Hsieh & Olken, 2014).[29]

The Contract Labor Act regulates contract labor use by firms with the main aim to prevent exploitation. It usually applies to establishments with 20 or more contract laborers. The act regulates the employment of contract labor by setting standards for their working conditions like fair wages and safety measures. While contract workers do not ordinarily count towards the threshold of IDA, but if a court holds the contract a sham and treats them as the principal employer's own workmen, then the employer can be penalized.[30] However,

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

[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 the 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, it shows the constraints imposed by the Act on firm growth.

[30]See: Bombay High Court Judgment

contract workers themselves provide flexibility to firms and have been shown to increase firm productivity (Hirsch & Mueller, 2012). Relaxation of threshold to hire contract workers, thus, can provide more flexibility to firms to hire them while reducing compliance burden.

Lastly, evidence shows that more punitive labor regulations decrease output and employment (Besley & Burgess, 2004; Aghion *et al.*, 2008) and constrain firm growth (Almeida & Carneiro, 2009). As firms grow, the chance of inadvertent breaches rises and if minor violations carry jail, managers can rationally reduce scale. For instance, criminal charges raise bargaining stakes during inspections, increasing non-productive costs. Thus, when routine compliance triggers criminal liability, firms can decide to stay small to reduce visibility.

4.1 Amendments to Labor Laws

States have the power to amend these acts in either pro-employer or pro-worker directions. Recently, these 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 amendments to the IDA increased the threshold for a firm to layoff workers and close an establishment without prior permission from 100 to 300 workers. The Contract Labor (Regulation and Abolition) Act was also amended to apply to establishments with 50 or more contract workers from the earlier threshold of 20. Some states have also decriminalized violations under these laws—making the environment less punitive and reducing potential harassment by inspectors. If these laws restrict manufacturing firms from attaining their optimal size, then these relaxations should spur firm growth.

To examine this, we exploit the amendments to the Factories Act, the IDA and the CLA, including any decriminalization, across states of India between 2009-2019. Five states amended these acts in a clear pro-employer direction largely—Rajasthan in 2014, Madhya Pradesh in 2015, Maharashtra in 2016, Jharkhand in 2017 and Uttar Pradesh in 2018.[31]

[31] However, the severance pay was also increased by twice the amount in a few states and the notice period increased from one month to three months (Bhattacharjea, 2021). This was a pro-employee amendment but relatively smaller as compared to other amendments by these states.

Rajasthan and Jharkhand amended all the three acts. Maharashtra amended the Factories Act in 2015 and enforced it from February 2016 onwards. It also amended the CLA and the IDA and enforced these from January 2017 and June 2017, respectively. Thus, we consider Maharashtra as a treated state from 2016 onwards. Uttar Pradesh amended the two acts—Factories Act, and the Contract Labor Act in 2017 and enforced these from 2018 onwards. It already had the 300 threshold for the IDA since 1950. Madhya Pradesh also amended the IDA in 2015.[32]

Along with these amendments, Rajasthan also made unionization more difficult. Rajasthan, Jharkhand and Maharashtra made violations under the Factories Act non-punishable by police arrest upon payment of a fine. Also, after the amendments, complaints against the employer regarding violation of any provisions under the Act would not receive cognizance by a court without prior written permission from the State government. Most states also provided an upper time limit for raising disputes with employers so that litigation is reduced.[33] Most states also increased permissible overtime hours by workers.[34]

Overall, these amendments largely relaxed the costs associated with non-compliance of provisions under these Acts apart from providing direct incentives for smaller firms to grow. Firms under the size of 100 could increase their size beyond the thresholds of 20, 40, and 100 with lower regulatory costs. It also provided the establishments that employed between 100 and 300 workers flexibility in hiring and firing workers. Firms beyond the size of 300 would benefit from decriminalization and the overall improvement in the local economy as output

[32] 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. However, Madhya Pradesh, Uttar Pradesh and Maharashtra simultaneously also amended the Factories Act to allow women to work night shifts in the manufacturing units. Hence, we consider robustness of our results to dropping these states from our analyses since the amendment of the night shift provision can also lend directly to increasing hiring of female workers in manufacturing establishments. We also drop the north-eastern states from the analyses, including Assam, due to sample sizes being small. We finally have 26 states and union territories in our analyses.

[33] 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.

[34] Additionally, Uttar Pradesh increased the threshold from 50 to 100 for firms not bound by overtime hour related regulations.

expands for smaller firms.[35]

If these amendments indeed spurred firm size growth, and an increase in firm size leads to an increase in relative female employment, then there would also be an increase in female employment in states that amended the labor laws. Next, we empirically examine this question.

4.2 Empirical Strategy

We estimate the causal effect of the amendments on firm outcomes using the ASI data on manufacturing firms and employing a difference-in-differences strategy. Specifically, we compare the change in firm 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:

$$Y_{ijst} = \delta_i + \delta_t + \delta_{jt} + \beta_1 Amendment^{\tau}_{st} + \epsilon_{ijst} \tag{5}$$

where Y_{ijst} refers to the outcome variable for firm i in industry j in state s in year t. Main outcomes include proportion of female workers and various firm size measures such as log of workers, employees and output. 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, $Amendment^{\tau}_{st}$, is an indicator variable that takes a value of one for states that amended 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) 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 state level since that is the unit of treatment. Since we have 26 states and union territories in our

[35] While there should have been a direct effect on the growth of firms sized less 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.

final analyses, we also estimate the wild clustered bootstrapped errors. β_1 gives the impact of the amendments on firm outcomes. 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. Moreover, between 2005-2009 there were changes in the indirect tax regime in India with many states adopting the new regime in a staggered manner. Thus, for our main analyses we use the time period 2009-2019.

A growing literature in the difference-in-differences design highlights the possible bias that can afflict the two-way fixed effects (TWFE) estimator when there is variation in the timing of treatment (Goodman-Bacon, 2021; Callaway & Sant'Anna, 2021; Sun & Abraham, 2021). This is due to two reasons. First, when the treatment effects are dynamic, i.e., they can change over time, previously treated units form a bad control group for units that are treated later. Second, weights attached to the treatment effects depend on the number of periods that a unit is observed as treated. Hence, given that the states amended the laws over a 5 year period, we use the estimator proposed by Callaway & Sant'Anna (2021). We prefer this estimator since it allows one to compute wild-clustered bootstrapped standard errors.[36]

Lastly, we also estimate the dynamic treatment effects before and after the amendments using the below event-study specification. This allows to test for parallel pre-trends—the crucial identification assumption in our empirical strategy.

$$Y_{ijst} = \delta_i + \delta_t + \delta_{jt} + \sum_{\tau=-4, \tau\neq -1}^{\tau=2} \beta_\tau Amendment_s^\tau + \epsilon_{ijst} \tag{6}$$

where, $Amendment_s^\tau$ 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

[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. Also, we do not use weights in the TWFE 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. Our results hold braodly with weights too.

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.[37] The year of the amendment is denoted as event time 0.

β_τ measures the impact of the amendments 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 β_τ 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.

Appendix Table A.9 compares the treatment states with the control states using data from years before 2014—the first year that a state amended the acts. We find that total employees in a firm are similar across the two states. Thus, pre-existing differences in firm size did not lead to certain states amending the acts vs the other states who did not amend them during this period.[38] However, the average value of output, profits, and productivity are higher in the treated states. These differences are possible due to differential industrial structures across the two states. Around 36 percent of the manufacturing units are in food processing and textile industries in the control states while only 26 percent units operate in these industries in the treated states. The treated states have a relatively larger share of industries in metals, electrical and transport related manufacturing. The latter set of industries also tend to traditionally employ less female labor as opposed to the former set, partly explaining the lower proportion of female workers in the treated states. The raw gap between the proportion of female workers is 9 percentage point across the two groups of states, and after accounting for differences in industrial structures reduces to 6.5 percentage points remains. Given the amendments were not directly targeting female employment, it is less likely that the changes to labor laws were endogenous to the female share of employment.

[37] The leads and lags are determined by the treatment years. Given that the first treatment occurred in 2014, the maximum number of periods after treatment are six. The last treatment was in 2018, and this makes the maximum number of pre-periods equal to eight. The binning of endpoints at -4 and 2 ensures that maximum treated states are included in the pre and post-period event window, respectively.

[38] Many states amended the acts after the pandemic to allow for more business-friendly environment, as the economic growth slowed down.

In the next section, we show that trends in female employment did not differ across the two group of states before the amendments. Nonetheless, we also use a matching estimator to check the robustness of our findings.

4.3 Impact of Amendments

Table 3 shows the impact of the amendments on the proportion of female workers in columns (1)-(2) using Equation 5. We find an increase in the proportion of female workers in a firm by almost 0.004 (or 4 percent of mean) when controlling for firm and industry-year fixed effects in column 2. Since, we have slightly less than 30 clusters, the wild-bootstrap clustered p-values are provided in brackets. These show that our estimates are marginally significant at 15 percent level. Figure A.6, panel (a), plots the event study coefficients obtained using this specification. We find no significant differential trends in the proportion of female workers in the treated versus the control states before the amendments were passed, but there is a significant positive impact 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 a consequence of relaxing firm size thresholds for the applicability of regulations. To examine this, we estimate the impact of the amendments on various firm size measures. Table 3, columns (3)-(4) show that total employees increase by 5.4 percent, and output by 19 percent after the amendments. Figure A.6, panels (b)-(c), plot the event study estimates for employees and output. These show a positive impact on employees and output after the amendments. While output effects are significant at 10 percent level, the positive effect on employment is significant at 15 percent level using the wild-bootstrapped standard errors clustered at state level. We find some pre-trends in the firm size measures in the treated vs control states before the amendments were enacted. However, we know that the standard DID estimates are not reliable when treatment is staggered.

To address the concerns earlier discussed with the TWFE strategy, we next use the alternate DID strategy proposed by Callaway & Sant'Anna (2021) to estimate the impact of the amendments on the outcome variables, with never-treated observations as the relevant control group. We plot the coefficients in Figure 2. With this alternative strategy 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), employees (panel b) and output (panel c) after the amendments.[39] The average treatment effect on the treated (ATT) is 0.005 increase (or 5 percent over the mean) in the proportion of female workers, statistically significant at the 5 percent level. The total number of employees and output significantly increase by 4 percent (at 15 percent significance level) and 13 percent (at 10 percent significance level) after the amendments, respectively. Importantly, we do not find pre-trends in any of the outcome variables. The standard errors are wild-bootstrapped and clustered at state level. Thus, the overall effects, taking into account the staggered implementation, are consistent with increasing firm size and relative female employment after the pro-employer amendments..[40] These results show that policy reforms that aid firm growth can also increase female employment.

4.3.1 Robustness

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

Matching: To allay any concerns that our post-treatment effects are solely being driven by differential pre-trends, we use the Synthetic Difference-in-Differences (SDID) method developed by Arkhangelsky *et al.* (2021). This method builds on the Synthetic Control (SC) method by Abadie *et al.* (2010). Broadly, it enforces the parallel trends assumption

[39] While imprecise, there appears to be, if anything, a decreasing trend in the proportion of female workers and firm size in the treated vs control states before the amendments.

[40] Notably, we also find a positive effect on raw materials used in production by around 20 percent after the amendments. On the other hand, we find a 2.2 percent increase in capital expenditure by firms; however, this is insignificant. This shows that firms expanded their output by increasing the use of labor and raw materials rather than capital.

by suitable control group construction, rather than assuming it.[41] To use this estimation method, we first construct a state-level panel dataset by averaging the outcome variables of interest for each state-year. This is because the SDID estimator requires a balanced panel, while the ASI data is an unbalanced firm-panel. The estimator then constructs a synthetic control group by using unit and time weights that balance treated and control group outcomes. It is important to note that, unlike the TWFE event study estimates, the SDID has no base event time — the dynamic effect at each time period is the absolute difference in the considered outcome between the treated and the synthetic control. Figure 3 plots the estimates for each time period before and after the treatment for the proportion of female workers (panel a) and firm size measures (panels b-c), after accounting for the staggered design. The bootstrapped-clustered standard errors plotted are suitable for small clusters. We find that none of the pre-treatment coefficients are significantly different from zero. There is a distinct increase in the proportion of female workers (panel a) by 0.003 (3.5 percent over the mean) and total employees by 6 percent after the amendments. While our findings hold even after using alternative estimation procedures that enforce parallel trend assumptions, however, the state-level aggregate estimates are less precise than using granular firm-level data.

Alternative female employment measures: To confirm our findings about increase in proportion of female workers due to the treatment, we also examine the effect of the amendments on measures of overall female employment and proportion of female mandays. Appendix Table A.10 reports the overall difference-in-differences estimates using the staggered estimation 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

[41] SDID differs from the SC method with regards to weighting and is generally considered superior due to its dual weighting scheme. It chooses unit weights to balance treated and control groups in pre-periods and then chooses time weights to focus on the subset of pre-treatment periods that best predict the post-treatment evolution of controls, before applying a DID-style comparison. This dual reweighting helps satisfy the parallel-trends assumption and can reduce bias when untreated units diverge over time.

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 1.3 percentage points. Given that 28 percent of firms employ women in our data, this is an increase of around 5 percent 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 0.005 (or 5 percent of mean).

Other checks: First, we drop each treated state one by one to examine whether one state drives our main findings. Appendix Figure A.7 plots the coefficients for the proportion of female workers in panel (a), log of employment in panel (b) and log of output in panel (c). The plots show that our main findings are not driven by any one state and we continue to find an increase in both female employment and firm size after the amendments. Next, we consider the entire data from 2001-2019 in our analyses and report the estimates in panel A.[42] Our findings continue to hold. Lastly, Panel (b) drops all treated states that extended the provision to work during the night shifts for women. Reassuringly, the increase in the proportion of female workers persists even after dropping these states. We also find an increase in output by 16 percent. However, the increase in employment, while similar in magnitude to our main findings is now less precise.

5 Mechanisms

In this section, we investigate the mechanisms behind the observed positive relationship between the proportion of female workers and firm size. As discussed in Section 2, three channels may explain this relationship: (i) provision of amenities by larger firms, which are

[42] As discussed earlier, we drop 1998-2005 due to incomplete product coverage in the initial years of the ASI data, changing product codes over time along with questionnaire changes, and more importantly changes in the indirect tax regime in India during 2003-2009 wherein states adopted the new tax regime in a staggered manner during these years.

valued relatively more by women, (ii) lower gender discrimination in larger firms, and (iii) change in task requirements across firm size that requires hiring of more women workers. As seen in the analyses of individual data (Table 2), 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. Additionally, the analyses using the ASI data involve gender disaggregated employment only for manufacturing workers, among whom task variation with size is likely to be limited. In fact, existing literature showing greater employment of women among exporting firms finds increased demand for women in non-production tasks as the main channel (Bonfiglioli & De Pace, 2021; Banerjee *et al.*, 2022). Next, we discuss the evidence behind the other plausible channels.

5.1 Amenities

In this section, we first examine whether women prefer workplaces with better amenities and what type of amenities these are. We then examine whether bigger firms are more likely to provide these amenities.

5.1.1 Do women differently value amenities?

We use the individual level survey data which captures amenities like— 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 use the revealed preference approach—if women are more likely to work in jobs with certian attributes then its is likely that they prefer those job attributes. 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 it. The dependent variable is whether 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 captured by the survey. 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 job with a written contract, and 2 percentage points more likely to work in a job where healthcare and maternity benefits are offered, relative to men. On the other hand, the availability of old-age support reduces the relative presence of female workers in a firm.[43] Second, existing literature also shows that women value amenities at workplace like flexibility, stability, work from home, safe transport, safe workplaces and childcare relatively more than men (Baker *et al.*, 2008; Mas & Pallais, 2017; Wiswall & Zafar, 2018; Bjorvatn *et al.*, 2025; Garlick *et al.*, 2025).

5.1.2 Do bigger firms provide better amenities?

Table 4 shows the relationship between firm size and job benefits. 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 percent) 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 percent) 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 percent and 45 percent, respectively. Thus, we find that most benefits, except part-time work, 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

[43]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 which benefits 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 of the firm. Again, we find that bigger firms are more likely to provide child care, free transport, and work from home, apart from other amenities. These amenities are shown to be valued relatively more by women as compared to men (Mas & Pallais, 2017; Wiswall & Zafar, 2018). A firm having at least 500 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 percent increase for benefits such as child care and 60 percent for free transport. The above evidence shows that bigger firms offer higher amenities that are typically 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. Appendix 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.[44] We find that an increase in total employees by 1 percent increases the welfare benefits per employee by 0.42 percent and per employee pension benefits by 0.38 percent (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 amenities. Thus, we next examine the association between firm

[44]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.

productivity measures and firm size in our data. Profits are deflated by two digit industry specific WPI with 2004 as the base year. Total Factor Productivity (TFP) is measured using 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) shows a positive relationship between firm size and all the three measures of firm productivity (profits per employee, labor productivity, and TFP) for both panel and cross-sectional estimates. The estimates show that profits increase by 1 percent, labor productivity by 0.58 percent, and the TFP by 0.05 percent when the firm size increases by 1 percent (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 certain amenities like creches or transport that women value more.

5.1.3 Impact of Labor Law Amendments: Amenities and Firm Productivity

Finally, we examine the effect of the labor law amendments on expenditure on amenities and firm productivity. Notably, since the amendments also led to a reduction in worker safety and health norms by reducing the number of firms regulated under the Factories Act, 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. This can enable them to attract workers rather than the external imposition of regulations that often invite harassment by labor inspectors (Amirapu & Gechter, 2020), further increasing costs suboptimally for them. 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 Appendix Table A.16 show that welfare expenditure per employee increase significantly after the amendments by

10 percent (column 1). However, for PF, the effect is insignificant while the magnitude is 9 percent. Profits per employee and output per employee also increase by 6.6 percent (columns 4 and 5). We find no significant increase in the TFP (column 6) after the 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 5 percent), profits per employee (by 9 percent), and labor productivity by 5.3 percent. The overall results are noisy, but the event study estimates show that the effects are dynamically increasing—showing that productivity measures can respond a few years later.

Taken together, these results show that an increase in firm size accompanied by higher amenity/welfare provision, after the amendments may have resulted in an increase in female employment after the amendments. 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 increase in firm size due to the amendments.

5.2 Impact of Labor Law Amendments: Alternative Channels

We test for alternative channels which could also explain the increase in female employment after the amendments. First, 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 a given state-industry after the amendments (Appendix Table A.17).

Second, we examine whether firms began exporting after the amendments since existing literature shows that exporting firms are more likely to hire female labor. The ASI data captures the share of output of a firm which is exported. The results in Appendix Table A.18 show that there was no increase in export share or the probability of exporting by firms after the amendments (columns 1 and 2). Third, we check whether amendments may have increased firm incentives to decrease contractual workers and substitute them with permanent workers. If women are less likely to work as contractual workers then this can potentially explain the change in female employment. The results in columns 3 and 4 of Appendix Table A.18 show that there was no significant decrease in use of contractual workers by firms after the amendments. Remember, the amendments also made hiring contractual labor less costly.

Third, the amendments may have increased turnover by easing layoff restrictions, with firms replacing unproductive incumbents with younger hires. This could partly explain the rise in female employment share if women constitute a larger share of younger job seekers. However, this channel is not applicable to firms having less than 100 employees—these firms always had the flexibility of freely firing workers. Therefore, to examine whether this could be a potential driver we test whether firms having size less than 100 in the pre-treatment period also show any change in outcomes. We define the pre-treatment period as before 2014 for the control states and as the years before the treatment year for the treated states to determine the firm size. Appendix table A.19 shows that firms sized less than 100 witness an increase in the proportion of female workers by 0.4 percentage point (or 4 percent of the mean) significant at 5 percent level. The increase witnessed by firms sized 100-300 is larger at 0.6 percentage point (or 5 percent of the mean). However, firms sized more than 300 witness the least increase in both the proportion of female workers (by 3 percent of the mean), which is insignificant, and firm size (insignificant for employment but lower and significant for output). These results are also in line with the fact that the eduction in compliance costs were largest for firms sized less than 300.

Lastly, could amendments have reduced the union power (which are dominated by males) and hence increased the possibility that women were able to get employment in these firms? Among all states, only Rajasthan made unionization more difficult. None of the other states passed any amendment regarding this. Previous results show that our results hold even after dropping Rajasthan. Thus, it is unlikely that changes in unionization is an important factor behind the observed increased in female employment after the amendments. Additionally, union density is very low in India—about 6.3% (Labour Bureau, 2020). Unionizations tends to increase with firm size and unions were historically more concentrated in large firms rather than small and medium sized firms (Pal, 2008). Since, its the latter set of firms that show the most significant increase in the outcomes, as discussed above, decreasing unionization is unlikely to be a channel. In fact, if firm size increases, unionization rates can potentially increase.

Taken together, these findings show 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.

5.3 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 females than males sort into bigger firms then without controlling for unobservable worker ability the gender wage gap can be smaller in bigger firms. Additionally, 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 (see Section 2 for a discussion). On the other hand, if bigger firms pay higher benefits that women value more, they can reduce the wages offered to female employees (compensating wage differential). 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 by gender in Table A.20 using the NSS and the PLFS individual employment data. Here, the dependent variable is the log of the daily wage rate.[45] 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

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

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 percent lower than men. However, women who work in firms of size 6-20 earn 36 percent lower wages, while those in firms with 20 and above employees receive 30 percent lower daily wages than men. While we control for demographic characteristics of women in our individual data (age, education, caste, religion, sector, and marital status), within a given industry-occupation and location, these are unlikely to control for the full extent of the selection effects arising from unobserved ability. 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.[46] The amendments also do not have a robust effect on the gender wage gap (Figure 4, panel (c)).[47] Given that firms experience an increase in their profits and provide higher amenities as their size grows (as seen in the previous section) without reducing relative wages to women, we can argue that lower discrimination in larger firms is not 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 the other 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

[46]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 percent when firm size increases by 1 percent When examining the relationship using the cross-sectional estimation, we again find an increase in the female-to-male wage ratio by 0.002 percent when firm size increases by 1 percent None of the estimates are significant, though.

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

profile. These were sent on consecutive weekdays. Additionally, based on the firm name, we obtained the number of employees of that firm in India through an online platform – *AmbitionBox*. In our final data, 497 firms 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 examined 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 percent 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 percent and the proportion of hired female workers by 4.2 percent

Using a simple theoretical framework, we argue that the more productive, larger firms find it profitable to provide amenities valued relatively more by women. These amenities increase female 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, child care, work from home, 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 bigger and 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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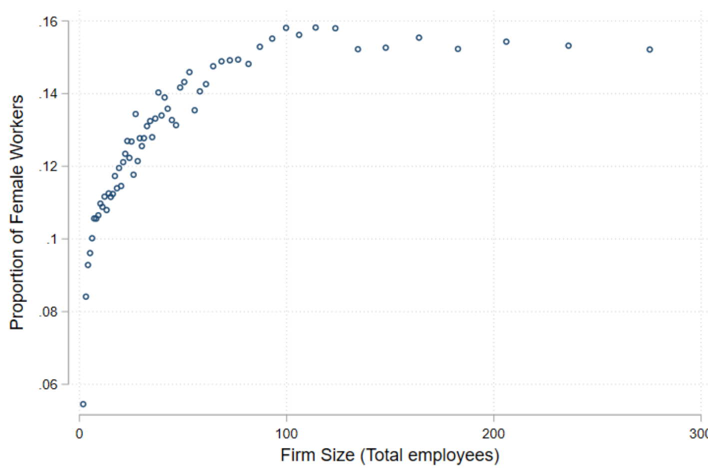
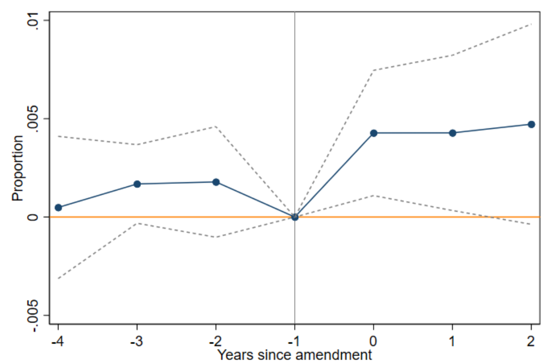
Figure 1: Proportion of Female Workers across Firm Size (ASI data)



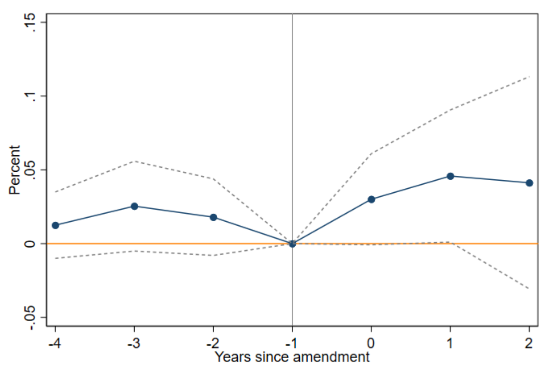
Notes: The figure plots the binscatter between the proportion of female workers and total employees in a firm across all enterprises.
Source: ASI 1998-2019.

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

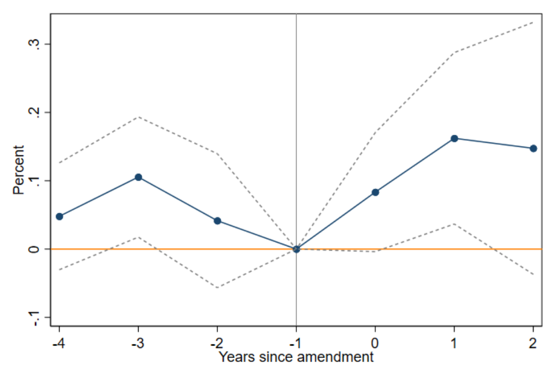
(a) Proportion of Female Workers



(b) Total Employees



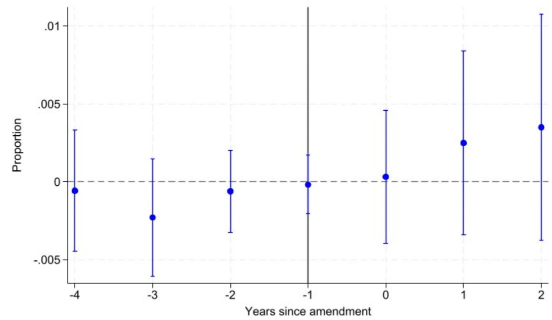
(c) Total Output



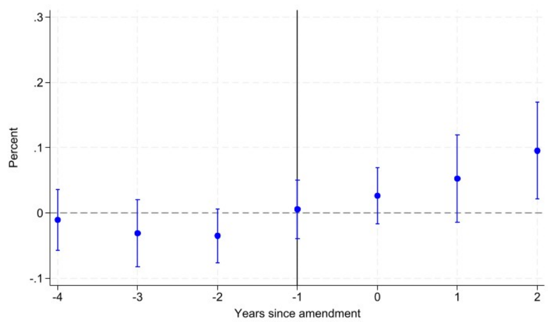
Notes: The above figures show event-study plots estimating the impact of state level amendments increasing the firm-size thresholds for applicability of the Factories Act and the Industrial Disputes Act using the (Callaway & Sant'Anna, 2021) estimator. The outcome of interest is the proportion of female workers (Panel a), (logged) number of total workers (Panel b), (logged) number of total employees (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 3: Impact of Amendments on Relative Female Employment and Firm Size (Synthetic DiD Event Study

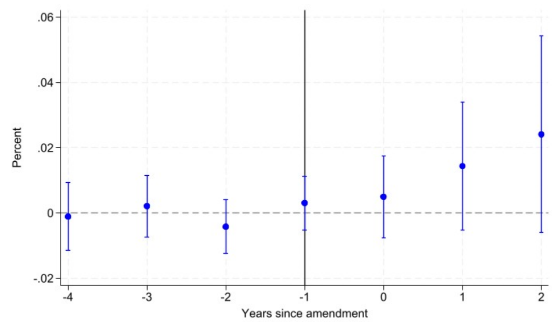
(a) Proportion of Female Workers



(b) Total Employees



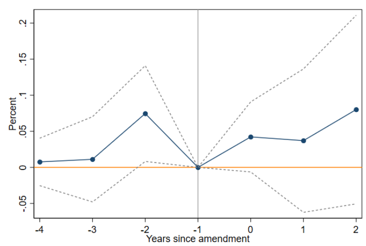
(c) Total Output



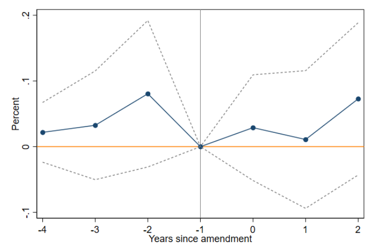
Notes: The above figures show event-study plots estimating the impact of state-level amendments increasing the firm-size thresholds for applicability of the Factories Act and the Industrial Disputes Act using the estimator Synthetic Difference-in-Differences (SDID) estimator developed by Arkhangelsky *et al.* (2021) and extended to an event-study framework by Clarke *et al.* (2024) and Ciccia (2024). The outcome of interest is the proportion of female workers (Panel a), (logged) number of total workers (Panel b), (logged) number of total employees (Panel c) and (logged) total value of output (Panel d). The unit of observation is the state-year, obtained by computing average value of the outcome variable across all establishments that report using some labor in a given state-year. Unlike traditional event study estimators, the SDID event-study framework does not rely on a designated base period. Instead, it estimates absolute effects—measuring the difference between treated and synthetic control groups at each event time. 95% confidence intervals for each estimate are plotted. Standard errors are bootstrapped at state level. The vertical line marks the year before the treatment occurs.
Source: ASI 2009-2019.

Figure 4: Impact of Amendments on Other Firm Outcomes (Staggered Event Study)

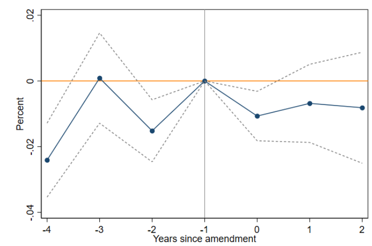
(a) Welfare per employee



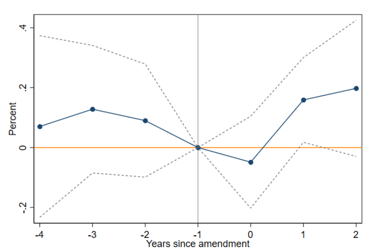
(b) PF per employee



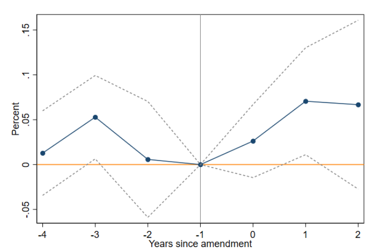
(c) Gender Wage Ratio



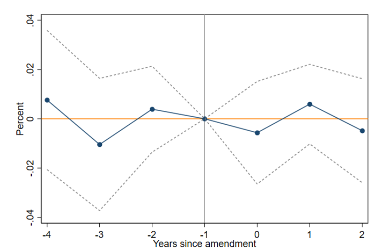
(d) Profit per employee



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

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

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

Notes: The table reports difference-in-differences estimation results for the outcome variables of relative female employment and firm size using two-way fixed effects. The dependent variable is proportion of female workers in columns 1-2, log total employees in column 3 and log total value of output in column 5. Treated states are Rajasthan, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are heteroscedasticity robust and clustered at the state level. ***, **, * show significance at 1%, 5% and 10%, respectively. P-values from wild-bootstrap clustering method are provides in square brackets.
Source: Annual Survey of Industries 2009-2019.

Table 4: Firm Size and Amenities (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

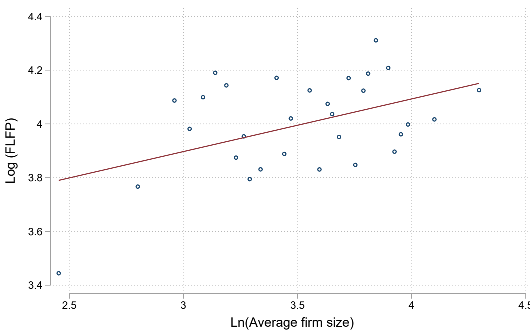
Notes: In column 1 the dependent variable takes a value of one when a worker is working part time and zero otherwise. In column 2 the dependent variable takes a value of one when a worker has a written contract and zero otherwise. In column 3-5 the dependent variable takes a value of one if the mentioned 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.

ONLINE APPENDIX

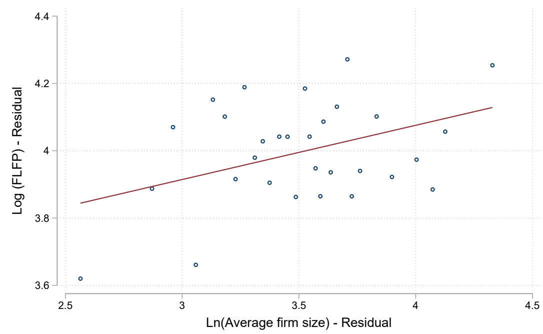
A Appendix: Figures and Tables

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

(a) No controls



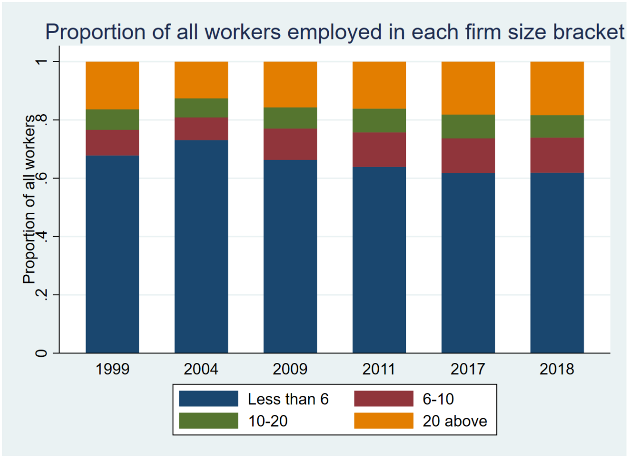
(b) Accounting for Income Per Capita



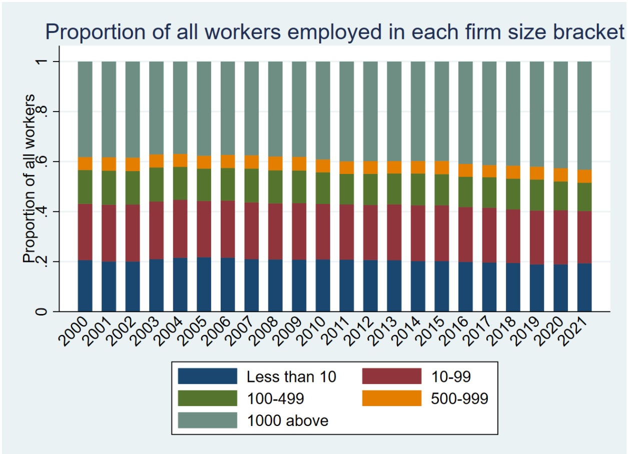
Notes: Panel (a) plots the binscatter of log of female labor force participation (FLFP) vs. the log of average firm size in the formal sector across countries. Panel (b) plots the binscatter of log of FLFP vs. the log of average firm size in the formal sector across countries, after controlling for the 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: Distribution of Workers by Firm Size Categories: India vs US

(a) India

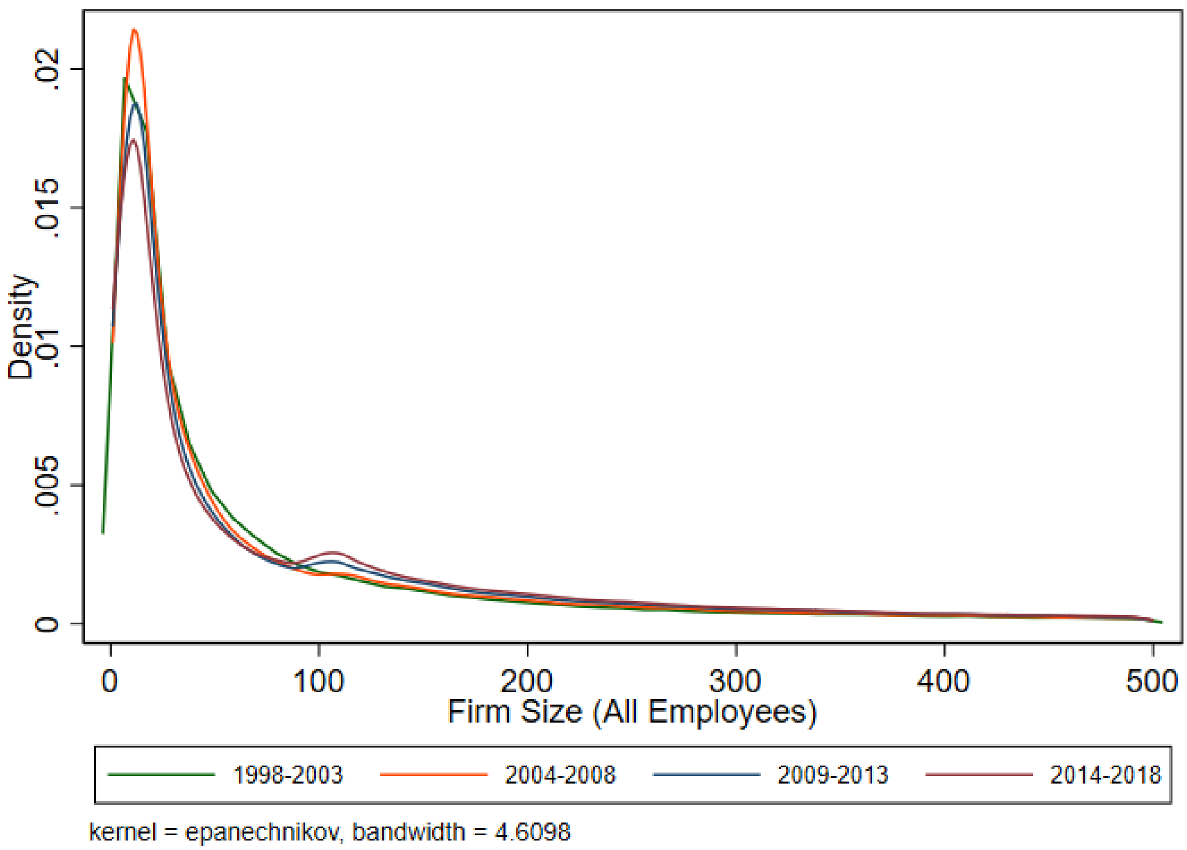


(b) USA



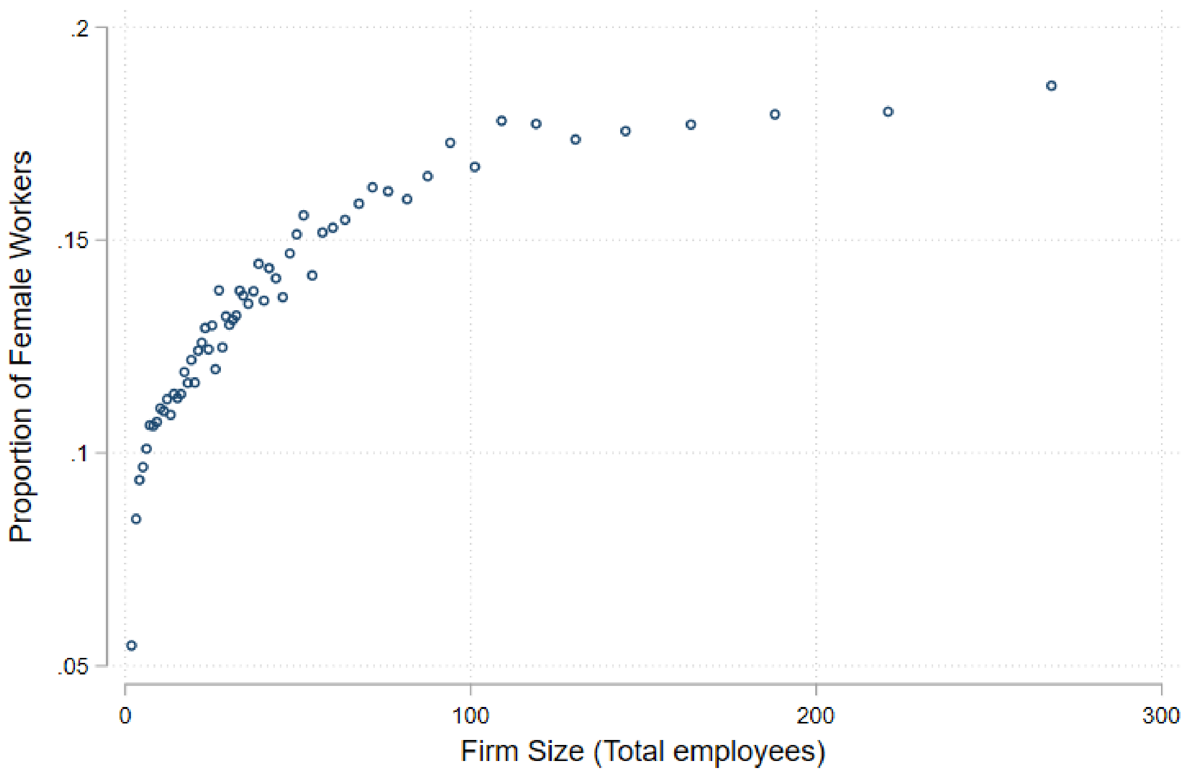
Notes: Panels (a) and (b) plot proportion of workers in each firm size category for India and the US, respectively.
Source: NSS and PLFS (India) and CPS (US), various rounds.

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



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

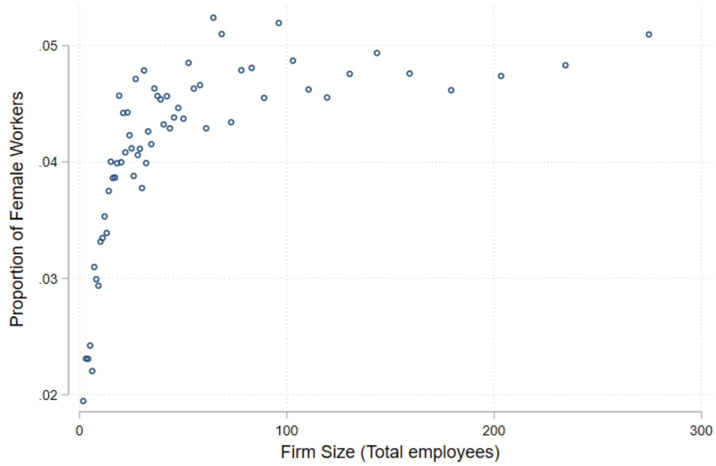
Figure A.4: Proportion of Female Workers across Firm Size (ASI data): Excluding Public Enterprises



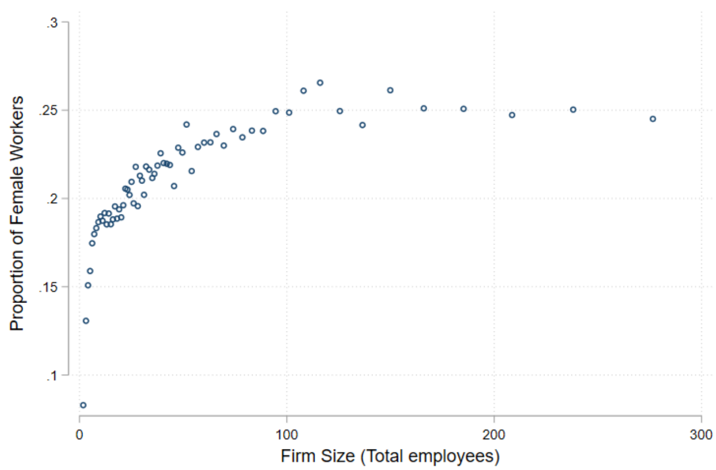
Notes: The figure plots the binscatter between the proportion of female workers and total workers in a firm after excluding public sector enterprises enterprises.
Source: ASI 1998-2019.

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

(a) Northern India



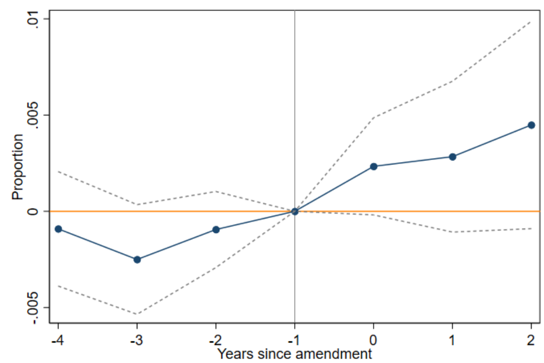
(b) Southern India



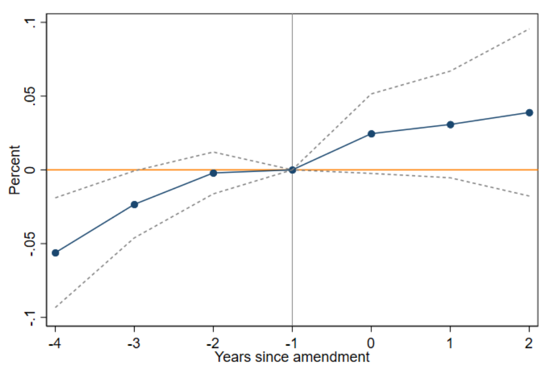
Notes: Panels (a) and (b) plots the binscatter between the proportion of female workers and total workers in a firm for the northern and southern states of India, respectively.
Source: ASI 1998-2019.

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

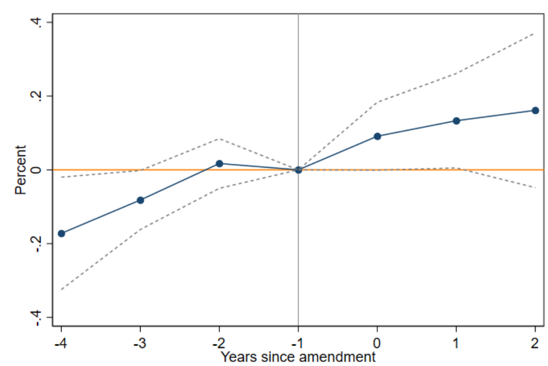
(a) Proportion of Female Workers



(b) Total Employees



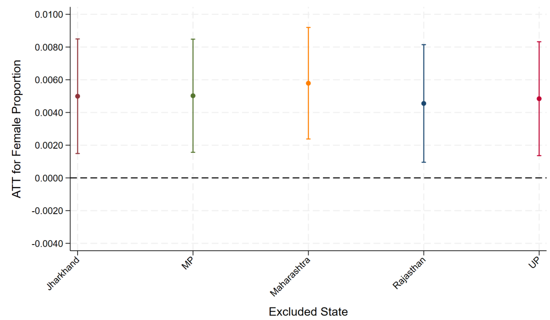
(c) Total Output



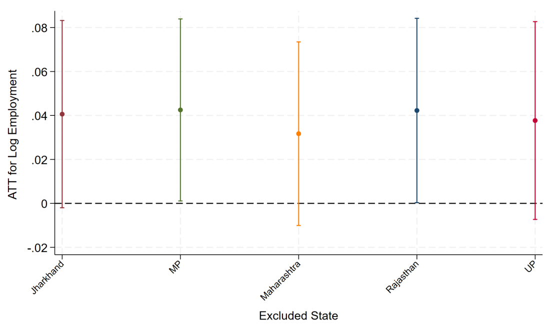
Notes: The above figures show event-study plots estimating the impact of state-level amendments increasing the firm-size thresholds for applicability of the Factories Act and the Industrial Disputes Act using the two-way fixed effects estimator. The outcome of interest is the proportion of female workers (Panel a), (logged) number of total workers (Panel b), (logged) number of total employees (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 A.7: Impact of Amendments on Relative Female Employment and Firm Size: Robustness (Dropping States)

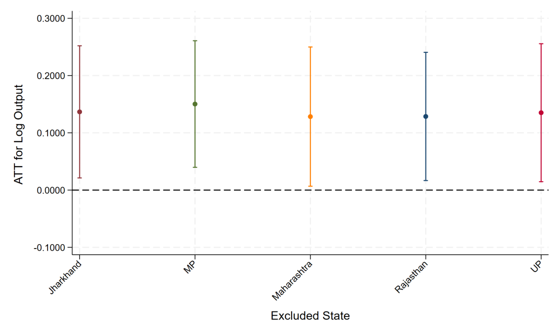
(a) Proportion of Female Workers



(b) Total Employees



(c) Total Output



Notes: The above figures show the average treatment effect on the treated of the amendments using 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 employees (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 90% confidence intervals. The treatment effects are with respect to the year before the amendment came into force (dashed vertical line). Specifications include establishment and year fixed effects. Standard errors are clustered by state.

Source: ASI 2009-2019.

Table A.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 (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)	2280.457	4488.016	954120
PF (INR, per employee)	3501.183	5406.843	954118
Gender Wage Ratio (female/male)	0.860	0.236	230141
Profit (INR, per employee)	90594.628	163397.053	901006
Labor Productivity (INR, output per employee)	1435557.829	1865492.456	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 (All Employees) refers to all employees including manufacturing workers, supervisors, other employees and contract workers. Firm size (Output) is defined as total value of output (price $\times$ quantity) produced by a firm deflated by two digit industry specific Wholesale Price Index (WPI) with 2004 as the base year. 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 A.2: Firm Size and Relative Female Employment (ASI data): Robustness to Alternative Definitions and Controls

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

Notes: The dependent variable is proportion of female workers in columns 1 and 3, and proportion of female worker mandays in columns 2 and 4. Firm size is defined as log of number of total employees in the enterprise in columns 3-4. In columns 1-2, firm size (Output) is defined as log of total real value of output. Export share capture the proportion of value of output that is exported by a firm in a given year. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted by establishment level survey weights. Standard errors in parentheses are clustered at firm level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Annual Survey of Industries 1998-2019.

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

	(1)	(2)	(3)	(4)
	Worker	Mandays	Worker	Mandays
5-10	0.039***	0.037***	0.039***	0.038***
	(0.002)	(0.002)	(0.002)	(0.002)
10-25	0.059***	0.057***	0.059***	0.058***
	(0.002)	(0.002)	(0.002)	(0.002)
25-50	0.075***	0.072***	0.073***	0.072***
	(0.003)	(0.003)	(0.002)	(0.003)
50-100	0.085***	0.082***	0.082***	0.080***
	(0.003)	(0.003)	(0.003)	(0.003)
100-300	0.094***	0.090***	0.090***	0.087***
	(0.003)	(0.003)	(0.003)	(0.003)
>= 300	0.104***	0.100***	0.097***	0.094***
	(0.003)	(0.003)	(0.003)	(0.003)
Mean Female Proportion	.121	.119	.121	.119
R-Squared	.8495031	.8558765	.8534086	.8592827
Observations	784652	682155	784521	682036
Firm FE	Yes	Yes	Yes	Yes
Indus. × 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 total employees. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted by establishment level survey weights. Standard errors in parentheses are clustered at firm level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Annual Survey of Industries 1998-2019.

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

Dependent variable:	Total				Hired	
	(1)	(2)	(3)	(4)	(5)	(6)
log (Firm Size)	0.070***	0.055***	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 Owner 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: Summary Statistics: Treatment vs Control States

	(1)	(2)	(3)	(4)	(5)	(6)
	Treated = 0			Treated = 1		
	Mean	SD	N	Mean	SD	N
Proportion of Female Workers	0.13	0.25	157146	0.04	0.14	63545
Firm Size (Employees)	78.23	430.27	157146	78.24	323.70	63545
Firm Size (Output)	1.03e+08	2.42e+08	157146	1.29e+08	2.73e+08	63545
Welfare (INR, per employee)	2333.80	4530.46	157145	2552.99	4704.35	63545
PF (INR, per employee)	3049.68	4815.61	157143	3757.20	5576.69	63545
Gender Wage Ratio (female/male)	0.85	0.24	49046	0.90	0.27	10043
Profit (INR, per employee)	101658.36	168011.20	148231	131082.73	190987.74	59164
Labor Productivity (INR, output per employee)	1485131.94	1885883.62	155671	1816444.85	2076292.03	63150
Total factor Productivity	35716.07	328674.72	146913	44953.08	250066.91	59847

Notes: Proportion of female workers are defined as total female workers in permanent employment out of total workers in permanent employment. Proportion of female mandays refer are defined as total female worker mandays in permanent employment out of total worker mandays in permanent employment. Firm Size (Employees) refers to all employees including manufacturing workers, contract workers, supervisors and unpaid employees. Firm size (Output) is defined as total value of output (price $\times$ quantity) produced by a firm deflated by two digit industry specific Wholesale Price Index (WPI) with 2004 as the base year. 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 2009–2019.

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

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

Notes: The table reports difference-in-differences estimation results for the outcome variables of firm size and female employment estimated using the method proposed by Callaway & Sant'Anna (2021). The dependent variable is an indicator variable that takes a value of one if a female worker is hired and zero otherwise in column 1, log number of female workers in column 2, proportion of female worker mandays in column 3 and proportion of female workers in column 4. Treated states are Rajasthan, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are bootstrap clustered at the state level. ***, **, *, # show significance at 1%, 5%, 10% and 15% respectively.
Source: Annual Survey of Industries 2009-2019.

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

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

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 employees in column 2, and log total value of output in column 3. Treated states are Rajasthan, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively in Panel (a). Madhya Pradesh, Maharashtra, Uttar Pradesh are dropped from Panel (b). 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 wild-bootstrap clustered at the state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Annual Survey of Industries 2009-2019 in Panels A and C and 2001-2019 in Panel B.

Table A.12: Amenities 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 employee	PF per employee	Gender Wage Ratio	Profit per employee	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 A.1. Firm size is defined as log of total employees in the enterprise. Controls in Panel B are organisation type, sector (rural/urban) and year of initial production. Each column reports the effective number of observations after incorporating the included fixed effects. Regressions are weighted by establishment level survey weights. Standard errors in parentheses are clustered at firm level for Panel A and at state-NIC (4-digit) level for Panel B. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Annual Survey of Industries 1998-2019.

Table A.15: Firm Size (output) and Other Firm Outcomes (ASI data)

	(1)	(2)	(3)	(4)	(5)	(6)
	Welfare per employee	PF per employee	Gender Wage Ratio	Profit per employee	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 A.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 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	0.101*	0.090	-0.003	0.066	0.066	-0.010
	(0.056)	(0.057)	(0.008)	(0.149)	(0.049)	(0.021)
R-Squared	.754	.817	.453	.477	.673	.755
Observations	462297	462293	121302	422431	456203	426248
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, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are 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.17: Effect of Amendments on Number of Firms (DID Estimates)

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

Notes: The table reports difference-in-differences estimation results for the outcome variables of number of firms in a given state, industry (nic 3 digit) and year. The dependent variable is number of firms in columns (1)-(2) and log number of firms in columns (3)-(4). Treated states are Rajasthan, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors 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.18: Effect of Amendments on Other Firm Outcomes (DID Estimates): Alternative Mechanisms

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

Notes: The table reports difference-in-differences estimation results for the outcome variables of share of exports in a firm's output (column 1), whether a firm exports (column 2), the log of contract workers hired by a firm (column 3) and the log of permanent employees (all employees excluding contract workers). Treated states are Rajasthan, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors 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.19: Impact of Amendments on Relative Female Employment and Firm Size: By Pre-Treatment Firm Size

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

Notes: The table reports difference-in-differences estimation results for the outcome variables of firm size and female employment estimated using the method proposed by Callaway & Sant'Anna (2021). The dependent variable is proportion of female workers in column 1, log total employees in column 2, and log total value of output in column 3. Panel (a) keeps firms having less than 100 employees in the latest pre-treatment period. Panel (b) keeps firms having between 100 and 300 employees in the latest pre-treatment period. Panel (c) keeps firms having at least 300 employees in the latest pre-treatment period. The pre-treatment period is defined as less than year 2014 for the control states and less than the year of treatment for the treated states. Treated states are Rajasthan, Madhya Pradesh, Maharashtra, Jharkhand, Uttar Pradesh in 2014, 2015, 2016, 2017 and 2018, respectively in Panel (a). Madhya Pradesh, Maharashtra, Uttar Pradesh are dropped from Panel (b). Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in brackets are bootstrap clustered at the state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Annual Survey of Industries 2009-2019.

Table A.20: 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.

B Model Details and Extension

B.1 Mathematical Details

In this section, we provide a detailed solution to the equilibrium condition described in Section 2.

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

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

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

First order conditions yield the following relationships:

$$\frac{\partial Y}{\partial N_m} = w_m(N_m) + \frac{\partial w_m}{\partial N_m} N_m \tag{B.2}$$

$$\frac{\partial Y}{\partial N_f} = w_f(N_f, a) + \frac{\partial w_f}{\partial N_f} N_f \tag{B.3}$$

The LHS of equations B.2 and B.3 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:

$$\frac{N_f}{N_m} = \left\{ \tau(z) \left\{ z_f(a) \right\}^{\frac{\sigma-1}{\sigma}} a^{\frac{\rho}{\epsilon}} \left\{ \frac{k_f}{k_m} \right\}^{\frac{1}{\epsilon}} \right\}^{\frac{1}{\frac{1}{\sigma}+\frac{1}{\epsilon}}} \tag{B.4}$$

The equilibrium wage ratio is given by:

$$\begin{aligned} \frac{w_f}{w_m} &= \left\{ \frac{k_m}{k_f a^{\rho}} \frac{N_f}{N_m} \right\}^{\frac{1}{\epsilon}} \\ &= \left\{ \frac{k_m}{k_f a^{\rho}} \right\}^{\frac{1}{\sigma+\epsilon}} \left\{ \tau(z) \left\{ z_f(a) \right\}^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\frac{1}{\epsilon}}{\frac{1}{\sigma}+\frac{1}{\epsilon}}} \end{aligned} \tag{B.5}$$

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:

$$\Pi(z) = \max_{a \in \{\underline{a}, \bar{a}\}} \left\{ \pi(z, \bar{a}) - C, \pi(z, 1) \right\} \tag{B.6}$$

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

$$\frac{\partial \pi^*(z,a)}{\partial z} = \left\{ N_m^{\frac{\sigma-1}{\sigma}} + \tau(z)\left\{z_f(a)N_f\right\}^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\sigma}{\sigma-1}}$$
$$+ z\frac{\sigma}{\sigma-1}\left\{ N_m^{\frac{\sigma-1}{\sigma}} + \tau(z)\left\{z_f(a)N_f\right\}^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{1}{\sigma-1}} \tau'(z)\left\{z_f(a)N_f\right\}^{\frac{\sigma-1}{\sigma}} \tag{B.7}$$

Here, 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 $\pi(\underline{z},\bar{a}) - \pi(\underline{z},1) < C < \pi(\bar{z},\bar{a}) - \pi(\bar{z},1)$[1], 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.

B.2 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.

[1] 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.

The profit function is rewritten as:

$$\pi(z, a) = \max_{N_m, N_f, a} Y(N_m, N_f, a) - w_m N_m - w_f N_f - C(a) \tag{B.8}$$

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:

$$N_m : \qquad \frac{\partial Y}{\partial N_m} = w_m \tag{B.9}$$

$$N_f : \qquad \frac{\partial Y}{\partial N_f} = w_f \tag{B.10}$$

$$a : \qquad \frac{\partial Y}{\partial a} = C'(a) \tag{B.11}$$

Substituting the functional forms yields the following:

$$N_m : \qquad z \left\{ (z_m N_m)^{\frac{\sigma-1}{\sigma}} + \tau(z) \left(z_f N_f\right)^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{1}{\sigma-1}} \left\{ (z_m N_m)^{-\frac{1}{\sigma}} z_m \right\} = w_m \tag{B.12}$$

$$N_f : \qquad z \left\{ (z_m N_m)^{\frac{\sigma-1}{\sigma}} + \tau(z) \left(z_f N_f\right)^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{1}{\sigma-1}} \left\{ \tau(z) \left(z_f N_f\right)^{-\frac{1}{\sigma}} z_f \right\} = w_f \tag{B.13}$$

$$\begin{aligned} a : \qquad & z \left\{ (z_m(a) N_m)^{\frac{\sigma-1}{\sigma}} + \tau(z) \left(z_f(a) N_f\right)^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{1}{\sigma-1}} \\ & \left\{ (z_m N_m)^{-\frac{1}{\sigma}} N_m z_m'(a) + \tau(z) \left(z_f N_f\right)^{-\frac{1}{\sigma}} N_f z_f'(a) \right\} = C'(a) \end{aligned} \tag{B.14}$$

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.9 and B.10, 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 $B.14$ 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.12 and B.13 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,

$$\begin{aligned}
\frac{\tau(z)\left(z_f N_f\right)^{-\frac{1}{\sigma}} z_f(a)}{\left(z_m N_m\right)^{-\frac{1}{\sigma}} z_m(a)} &= \left\{\frac{N_f}{N_m}\frac{k_m}{k_f a^\rho}\right\}^{\frac{1}{\epsilon}} \\
\implies \frac{N_f}{N_m} &= \left\{\tau(z) a^{\frac{\rho}{\epsilon}} \left(\frac{z_f(a)}{z_m(a)}\right)^{1-\frac{1}{\sigma}} \left(\frac{k_f}{k_m}\right)^{\frac{1}{\epsilon}}\right\}^{\frac{\sigma\epsilon}{\sigma+\epsilon}} && \text{(B.15)} \\
\frac{w_f}{w_m} &= \left\{\left\{\tau(z) a^{\frac{\rho}{\epsilon}} \left(\frac{z_f(a)}{z_m(a)}\right)^{1-\frac{1}{\sigma}} \left(\frac{k_f}{k_m}\right)^{\frac{1}{\epsilon}}\right\}^{\frac{\sigma\epsilon}{\sigma+\epsilon}} \frac{k_m}{k_f a^\rho}\right\}^{\frac{1}{\epsilon}} && \text{(B.16)}
\end{aligned}$$

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:

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

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/urban location, and initial year of production (X_{ijst}). All regressions are weighted by the provided probability weights. The standard errors are clustered at the firm level for the panel estimates and

[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.

state-NIC level for cross-sectional estimates.[2]

C.2 Individual data

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

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

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

[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 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 India's topmost platform for job search. We created eight fictitious profiles – two per role, one male and one female. These were created to have equivalent qualifications and experience and be similar in every aspect except gender. These profiles were used to systematically apply to job postings for three months, during consistent timings on weekdays. We detail the process of profile creation, job selection, application, and recording callbacks from employers below.

D.1 Creating Fictitious Profiles

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

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

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

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

D.2 Selection of Jobs

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

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

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

D.3 Applying to Jobs

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

D.4 Recording Responses to Applications

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

D.5 Callback and Response Rates

The total number of applications sent was 9238 (4619 for men and 4619 for women). Appendix Table D.1 reports the callback rate, calculated as the proportion of positive callbacks received to the total number of applications sent ($\frac{\text{Number of Positive Callbacks}}{\text{Number of Applications}}$). The overall callback rate for women across all roles is 3 percent, compared to 3.8 percent for men. A pairwise t-test confirms that this difference is statistically significant. We submitted 800 applications to the BPO role, 1,974 to Finance, 1,918 to HR, and 4,846 to Sales and Marketing. The table shows that women generally receive a lower callback rate than men across all roles except HR, where the callback rate is slightly higher for women. This is in alignment with findings from previous studies, which have also indicate that women are often preferred for female-dominated sectors. In the BPO sector, a gender neutral job role, the callback rate for women equals men. On average, smaller firms have higher callback rates than bigger firms – possibly because bigger firms receive more applications since candidates may find them more attractive.[1] Notably, female profiles with similar skills are less likely to receive a callback from larger receive compared to comparable male profiles (1 percentage point lower callback rate).

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

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

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 500,000 INR, 490,000 INR, and 560,000 INR, respectively. The salary differential only seems to arise from the largest category, while the first two firm size categories are similar to each other.

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

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

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 51–200 employees, and the third level includes firms with more than 200 employees. Standard errors, shown in parentheses, are clustered at the job-ID level. Significance is indicated by ***, **, and * for 1%, 5%, and 10% levels, respectively.