Department of Economics, University of Warwick

Monash Business School, Monash University

as part of

Monash Warwick Alliance

Does Removing Restrictions on Night Shifts for Women Workers Improve Their Labour Market Outcomes? Evidence from India

Sai Shreyas Krishna Kumar

Warwick-Monash Economics Student Papers

March 2024 No: 2024/66

ISSN 2754-3129 (Online)

https://warwick.ac.uk/fac/soc/economics/research/wmesp/

Recommended citation: Krishna Kumar, S. S. (2024). Does Removing Restrictions on Night Shifts for Women Workers Improve Their Labour Market Outcomes? Evidence from India. *Warwick Monash Economics Student Papers* 2024/66.

[1] Warwick Economics would like to thank Gianna Boero and Samuel Obeng for their contributions towards the selection process.

Does Removing Restrictions on Night Shifts for Women Workers Improve Their Labour Market Outcomes? Evidence from India

Sai Shreyas Krishna Kumar*

Abstract

I study the effect of lifting restrictions on night – shift work for women on their labour market outcomes. Using the staggered repeal of night – shift restrictions for women under the Factories Act, 1948 in the Indian states of Punjab, Gujarat, Maharashtra, and Assam, I employ a Triple Difference model to estimate its effect on the share of women workers and daily wages for women in manufacturing. My results suggest no significant impact as the estimated effects are close to 0 and statistically insignificant. I am also able to rule out effects larger than 0.95 p.p and 2.8% on the share of women workers and daily wages respectively, and these estimates are robust to the use of the Stacked Triple Difference regression. I also provide several possible explanations for my results using case studies.

Keywords: Night Shifts, Female Labour Force Participation, Wages, Manufacturing, India

JEL Classification: J08, J16, J21, J31, J38, K31, O14, O25

---

* Contact: saishreyaskk@gmail.com. I would like to profusely thank Prof. Manuel Bagues for all the support and guidance and without whom this paper would not have been possible. I would like to thank my family and friends for their constant support. Online Appendix and replication package can be accessed here.

1. Introduction

India has for long restricted night - shifts for women workers. In the manufacturing sector, women have not been allowed to work in night – shifts ever since the Factories Act 1948 came into effect. The rationale that governments have used for such measures is to ensure that women are protected. There is evidence to suggest that more accidents take place during night – shifts, and therefore it has been deemed to be harmful (Kostiuk, 1990). However, these kinds of restrictions are not unique to India, but also exist in Taiwan, Japan, and several other countries (Kato & Kodama, 2018). Importantly, similar restrictions have been ratified by the International Labour Organisation, and therefore many legislations of this kind derive their legitimacy from this convention (Zveglich & Van Der Meulen Rodgers, 2003).

However, India's female labour force participation has been consistently declining, and this continues to be a serious challenge for policy makers (Mehrotra & Parida, 2017) (Klasen & Pieters, 2015). In this context, restricting night - work could be one of the factors that limit women, especially low – skilled women workers, from being employed in manufacturing (Gartenberg & Bandekar, 2011). This paper studies how removing night – shift restrictions could impact female labour market outcomes. I exploit a natural experiment in India, where four states, Punjab, Gujarat, Maharashtra, and Assam lifted this restriction between 2013 and 2016. There is limited empirical evidence on how allowing night - work for women could affect their labour market outcomes in India, and the effect is ex-ante unclear.

On the one hand, there is the more conventional story that women may be unable to take up night – work owing to household responsibilities and safety concerns (Kaiwar, 2014). Therefore, removing such restrictions could be ineffective in improving female labour force participation and could potentially lead to them dropping out from the workforce (Kato & Kodama, 2018). On the other hand, restricting women workers from doing the night – shift means that factories cannot utilize their female workforce efficiently, especially during periods of high demand. This would mean that the cost of hiring women workers for factories would be higher, which disincentivizes them from hiring women (Kato & Kodama, 2018) (Zveglich & Van Der Meulen Rodgers, 2003). Removing such restrictions could potentially lead to an increase in the employment of women in factories.

I test the effect of lifting the restriction in the manufacturing sector by assembling data from the Annual Survey Industries, a nationally representative survey of factories registered under the Factories Act 1948, for the period 2008-09 to 2018-19. I then identify industries which require women working in night – shifts, and identify 5, namely, textiles, food products, leather products, beverages, and apparel. Subsequently, I estimate a triple difference model to estimate the effect of lifting the restriction on the share of women workers and daily wages in night – shift industries. My choice for these outcome variables rests on assumptions regarding the elasticity of female labour supply in India. If female labour supply is elastic, I would expect to see an increase in the share of women workers, while in the case of inelastic female labour supply, I would expect to see an increase in wages, if the policy was indeed effective.

The estimates obtained suggest that lifting the night – shift restriction was ineffective, as I find effects on the share of women workers and daily wages to be close 0, and statistically insignificant. The standard errors are small, indicating that the estimates are relatively precise. I am also able to rule out effects larger than 0.95 percentage points (equivalent to effects larger than 8.4%) on the share of women workers and effects larger than 2.8% on daily wages. I also show that these results are robust to the use of the Stacked Triple Differences model to account for potential biases due to staggered adoption as outlined in Goodman – Bacon (2021), and to various other robustness checks.

Using two previous qualitative case studies on factories in Tamil Nadu and the call – centre industry in India, I provide several possible explanations for my results. One, women may not necessarily be averse to working the night – shift, but it is contingent on adequate safety measures being in place and tangible improvements in economic status in the form of higher wages, which was not the case in TN, and potentially was not the case in the states I consider as well, which could explain why I do not see an increase in the share of women workers. Furthermore, investment in safety related infrastructure could either disincentivize or significantly delay factories from employing even existing women workers in night – shifts, and this could explain why I do not see an increase in daily wages.

1.1 Contribution

This paper contributes broadly to two strands of literature. Firstly, it contributes to literature pertaining to the effect of restricting working hours on labour market outcomes for women. Gupta (2021) uses the exogenous tariff reductions due to the 1991 liberalisation reforms and finds that firms in industries which saw an average decline (defined as 115%) in tariffs saw a reduction in the share of women workers by 40%. This was because lower tariffs meant that firms faced higher competition, which led to a 7% increase in the number of shifts (which is equivalent to 22 extra shifts). This decline was more pronounced in firms which had multiple shifts before 1991, where an average tariff decline saw a 65% decrease in the share of women workers, indicating that the restriction on night – shifts for women (which also prevents them from working overtime) led to a reduction in the share of women workers, especially after 1991. This is in line with the findings of Zveglich and Van Der Meulen Rodgers (2003), who exploit a natural experiment in Taiwan, where restrictions were imposed on overtime work and night – shifts for women in Taiwan and find that it led to a decline in female working hours by 6.1% and a 1 p.p decline in female employment, but no significant impact on wages.

On the other hand, Kato and Kodama (2018) estimate the impact of relaxing overtime restrictions for women under the Labour Standards Act 1947 in Japan. They use a DD identification strategy with industries where this restriction was lifted as a treatment group, and those which continue to be restricted as a control group and find that lifting the restriction led to an increase in female employment. While the law also lifted night – shift restrictions in some industries, this did not have a significant impact on female employment, as most industries were already permitted to employ women in night – shifts. My paper contributes to this area of literature by specifically estimating the potential impact of lifting night –shift restrictions, in a context where there was a complete ban on night work, which would provide more reliable estimates of lifting such restrictions as compared to Kato and Kodama (2018)

I also contribute more broadly to literature on the issue of declining female labour force participation (FLFP) in India and policy measures to address this issue. Klasen and Pieters (2012) find differential effects based on the education levels of women. Among the less-educated women, employment opportunities grew marginally owing to declining employment for men, and they mostly worked in low – wage jobs in the garment industry or as domestic workers. On the other hand, well – educated women had jobs that were more secure and well paid in the services sector or were self – employed. Mehrotra and Parida (2017) explicitly find a negative association between primary and secondary education and female labour force participation, but a positive effect of graduate education. This could potentially be explained by the U – Shaped relationship between education and FLFP, wherein women at the middle of the education distribution do not wish to take up low – skill jobs in manufacturing, owing to social stigma, but are not qualified enough to take up high - skilled jobs in services (Klasen & Pieters, 2015) (Rustagi, 2013)

An alternative explanation for declining FLFP in the literature is that women opt out of the workforce either due to increases in overall wealth and incomes of other household members or due to childbearing responsibilities (Sarkar et al., 2019) (Bhalla & Kaur, 2011). Both papers find a significant negative impact of a male spouse's education level on FLFP, as women married to males who are highly educated and earning substantial incomes are found to be dropping out, as they do not wish to engage in low – skilled work thereby earning lower wages, which could affect the household's social status (Bhalla & Kaur, 2011). Contrary to this, some argue that declining FLFP is owing to volatility and inadequate jobs for women. While the manufacturing sector is seeing a rise in women workers as shown in Mehrotra and Parida (2017) and Klasen and Pieters (2015), jobs in the sector continue to be inadequate and volatile as shown by Deshpande and Singh (2016). My paper adds another dimension to this literature, by looking at how reforming existing labour laws in India could improve the involvement of women, and especially low-skilled women in the labour market.

The rest of the paper is organized as follows. Section 2 details the policy context on night – shifts for women, focusing on the Factories Act 1948, and provides case studies on TN and the call centre industry. Section 3 outlines the theoretical framework for my empirical analysis. Section 4 provides details on the dataset, namely Annual Survey of Industries, and Section 5 explains my identification strategy. Section 6 describes the key results from my model, and Section 7 outlines some threats to the validity of the estimates and shows robustness checks to rule them out.

2. Background on Night – Shift Work for Women

2.1 Policy Context

The Factories Act 1948 is the primary legislation in India that sets out the rules for employing workers in factories. It first came into existence in 1881, during the British rule, and was subsequently amended several times. The 1948 version (passed post India's independence) is the most comprehensive version and lays out detailed rules related to health, safety, working hours, the employment of young persons (children and adolescents), and penalties for contravening the provisions of the Act. Despite several amendments, one provision that has stayed on is the prohibition on employing women workers after 7PM, under Section 66(1)b of the act (Ganashree, n.d.). This provision has been controversial and was challenged for the first time in the Madras High Court in a case titled "*Vasantha R. Vs Union of India and Ors*" in 2000. The petitioner in this case was a woman worker R. Vasantha, who worked in a textile mill in the Dharmapuri district in Tamil Nadu and demanded that she be allowed to work the night shift, as long as reasonable steps are taken to ensure her safety. The Madras High Court struck down this provision and argued that this was in violation of Article 14 and 15 of the Indian constitution which guarantees equal rights for all citizens, without discrimination on the basis of gender. The court also laid down safety guidelines for all women to work, which include securing written consent from the worker, ensuring CCTV cameras and the presence of adequate security personnel and transportation at night if required (Padmanabhan, 2000).

Ever since this judgement, women workers have been working in Tamil Nadu in the night shift. Since then, there was a demand to enact a law to allow women across India to work in night shifts. In 2005, consultations began with various stakeholders as an amendment to this effect was approved by the cabinet of the Government of India, but it was never passed in Parliament[1] (Kaiwar, 2014). In some Special Economic Zones[2], women were allowed to work in the night – shift, and a few women indeed opted for the night shift in some cases (Aggarwal, 2012). In 2014, after the election, a new set of labour codes were proposed (they were eventually passed in 2020 but are yet to be implemented) which revived the debate on allowing night – shifts for women. Since, the Madras High Court Judgement went unchallenged in higher courts and the demand for allowing night shifts for women grew among manufacturers as well as Labour Unions, this set the precedent for several states to lift this restriction, as the act allows state governments to frame rules though a notification. To this end, Punjab amended the act in 2014, Maharashtra in 2015 and Assam in 2016 to allow night – shifts for women in factories. As in the case of Tamil Nadu, a case was filed by a food processing firm in the Gujarat High Court in 2013, and the High Court struck down section 66(1)b, allowing women to be

[1] A National Commission for Women report titled "Night Shift for Women" incorrectly mentions that this amendment was passed by the Parliament, but this was not the case.

[2] Special Economic Zones are designated areas in different parts of India where businesses are encouraged to set up, and they are provided with a number of incentives for this such as tax cuts, improved infrastructure, and exemption from duties, among others.

employed in night shifts. All the states laid down safety guidelines, as mentioned in the Madras High Court judgement. Figure 1 illustrates the states which lifted the night – shift restriction in a map. Note that Tamil Nadu could not be included in my analysis as a treated state owing to unavailability of data.

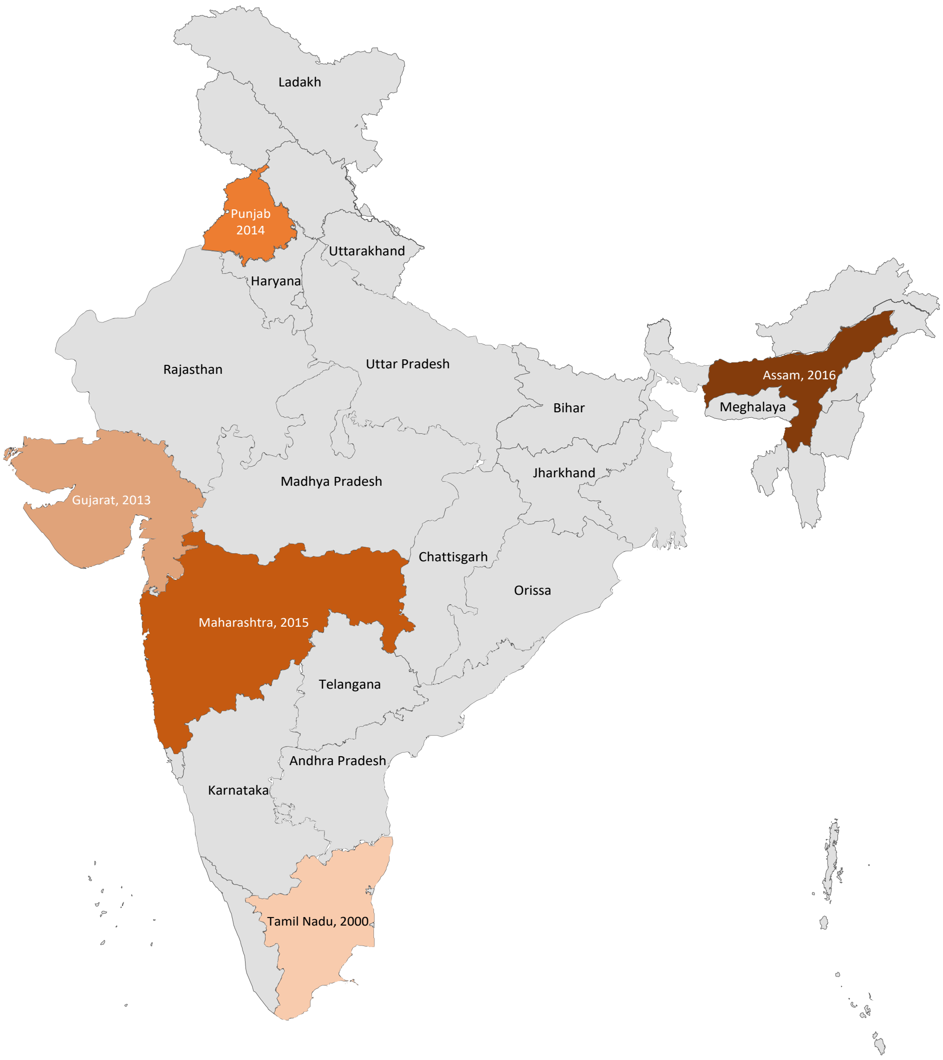


FIGURE 1: MAP SHOWING STATES WHICH LIFTED THE NIGHT SHIFT RESTRICTION

Notes: The figure shows the states which lifted the restriction in the Factories Act, 1948 on night – shifts for women workers in a map. In this map, Andhra Pradesh and Telangana are shown as separate states, though I consider them as one state (as was the case before 2014). Similarly, Jammu and Kashmir and Ladakh are shown separately, based on the constitutional amendment in 2019, but I consider them as a single state.

2.2 Case Studies

2.2.1 Textile Industry in Tirupur Industrial Cluster and Special Economic Zones in Tamil Nadu

As mentioned previously, the Madras High Court held that the ban on night – work for women was unconstitutional and struck it down, and ever since then, women workers have been allowed to work in night – shifts in Tamil Nadu. Narasimhan and Sethi (2014) published a short qualitative case study in the *Business Standard* newspaper on the garment workers in the industrial cluster of Tirupur, where nearly 250,000 women workers work. Here, the factory owners, workers and the government have consensually developed rules overtime, in line with the High Court judgement, to ensure that women working in the night – shift are safe. Some firms provided accommodation facilities, security, and transportation facilities for women working in night – shifts. However, one of the stakeholders interviewed in the case study points out that women were employed for night – shifts only during periods of high demand, when production was scaled up, and not on a regular basis as many women preferred not to work at night. Furthermore, a cause for concern was that some of the safety norms laid down by the court were not followed. Several factories did not have a sexual harassment cell or female supervisory staff, which potentially disincentivizes women from working the night – shift.

Kaiwar (2012) documents that in the Special Economic Zone in Chennai, even if women were willing to, they were not allotted the night – shift in some cases, especially if the factory closes midway through the night, as this would mean they would have to leave late at night, and this was considered unsafe. Furthermore, in some cases, women had to do more night – shifts in a month as compared to men as they could not work for the entire period of the night – shift, again owing to safety concerns. In both case studies, women workers were divided on night shifts, with some in favour of it and others against it.

2.2.2 Call Centres in India

Information Technology and the Telecom industry has seen an increase in the number of women workers since the 1990s. Due to the nature of the work, a large number of women have been working in night – shifts (Gothoskar, 2006). A qualitative case study of women workers in call – centres by Singh and Pandey (2005) suggests that women workers worked in night shifts, owing to higher wages. The study also provides evidence that the perception of women – working in night – shifts is gradually changing, with many households, including low – income households, viewing it positively as it improves financial stability for the household. This has outweighed the social stigma associated with women working at night, to some extent. However, most of the women working in the industry were single women, as marriage brought with it household responsibilities which was not compatible with night work.

3. Theory

I explore two mechanisms of how allowing night work for women could affect female labour market outcomes. First, I first consider the case where female labour supply is elastic. If the policy was effective, elastic female labour supply would mean that the share of women working would increase, as night – shifts would require more women to be employed.

Next, I consider the case where female labour supply is inelastic. If the policy was indeed effective, this would potentially result in higher wages for women, as existing women workers would be incentivized to work at night by being offered wage premiums (Koistiuk, 1990) (Debeuomont & Nsiah, 2010).

Furthermore, I assume that male and female workers are close substitutes in factories, which is in line with Acemoglu et al. (2004). This assumption ensures that factories do not choose male workers over female workers even after the restriction is lifted owing to a low elasticity of substitution.

4. Data

I use the Annual Survey of Industries (ASI), a nationally representative cross – sectional survey of factories registered under the Factories Act, 1948, and therefore affected by the natural experiment I exploit. The survey is conducted on an annual basis and collects data on a variety of factory – level indicators, including indicators pertaining to employment, relevant for my analysis. I compile these cross – sections from 2008 – 09 to 2018-19. Figure 2 presents the sample – size in each cross – section I consider for my analysis.

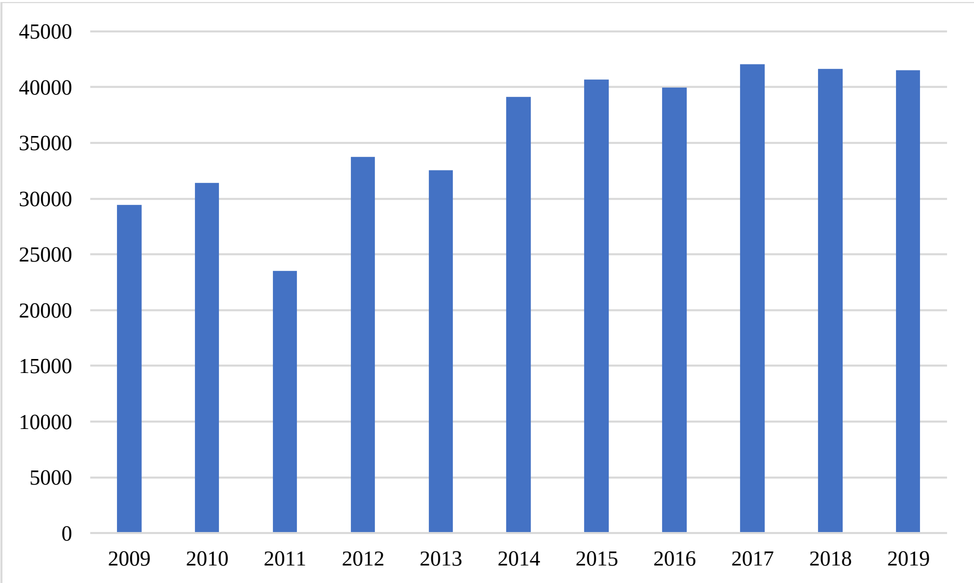


FIGURE 2: ASI SAMPLE SIZE BETWEEN 2009-19

Notes: The figure shows the number of factories surveyed by the Annual Survey of Industries between 2008-09 and 2018-19.

Though my dataset is a repeated cross – section of factories, I track 36 industries, which I identify using the 2 – digit National Industrial Classification (NIC) code[3] and 31 states[4] across the entire time period. Tables A1 and A2 in Appendix A provide the full list of states and industries I track each year along with summary statistics. Details on the construction of the dataset and the sampling procedure used by ASI are given in Appendix C.

[3] The National Industrial Classification assigns codes for each industry across all sectors in India, and has been developed by the Ministry of Statistics, Government of India

[4] I also include 4 Union Territories in this list (namely Pondicherry, Andaman & Nicobar Islands, Daman & Diu, and Dadra & Nagar Haveli), and I will refer to these as states in my paper. Furthermore, the formation of Telangana as a separate state from Andhra Pradesh in 2014 meant that both were coded as separate states from 2014. I however consider undivided Andhra Pradesh, and factories coded as belonging to Telangana are coded as Andhra Pradesh.

Outcome Variables

Share of Women Workers: The survey provides a breakdown by gender of the number of workers (which is labelled as "average persons worked") who are directly employed by the factory. Furthermore, it also provides the number of contract workers and supervisory staff, however, these are not disaggregated by gender. However, these account for only 12.5% of the total workers. Therefore, I drop these categories, and only use data on workers employed directly by the factory. I first calculate the total number of workers employed and calculate the share of women workers by dividing the number of women employed by the total number of workers.

Daily Wages: I use wages as an outcome variable as I do not have data on the number of hours worked, and therefore if the policy was effective, I could see an increase in wages as women can work an additional shift. The survey provides wages paid for the year for each type of worker mentioned above. Again, only wages for workers employed directly by the factory are disaggregated by gender. Furthermore, it provides data on the number of "mandays" worked by female workers. This is defined as the total number of workers working across all shifts in a day summed over all working days in the year, again disaggregated by gender. I calculate daily wages for women workers by dividing the total wages paid for the year by the total mandays worked by women, which gives us the daily wage per worker.

Control Variables

Fixed Assets: I use data on various fixed assets reported by each factory. The survey reports the opening and closing value of fixed assets in Indian Rupees for each year. In order to control for capacity expansions over the years, I use the closing value of land, building and plant and machinery.

Working capital: The closing and opening value of total working capital in Indian Rupees is reported in the survey. I use this to control for changes in liquidity and financial health over time. This not only affects employment by ensuring that the business and production process are carried out efficiently but is crucial to sustain a workforce and pay wages on time, and any potentially changes over the years could affect the labour market, as was seen in 2016 during the demonetisation exercise (Deshpande & Singh, 2020)

Sales: Total annual sales data are reported in Indian rupees in the survey. This again could potentially affect profits over the years and takes into account any changes or shocks over time in the market, such as changes in demand and consumer preferences, which could in turn affect labour market outcomes.

Table 1 and Table 2 below provides summary statistics for all the outcome variables and control variables used in my empirical analysis. An interesting point to be noted is that the policy was adopted by states, with a significantly lower share of women workers, though daily wages are largely the same across the treated and control states.

TABLE 1: SUMMARY STATISTICS FOR TREATED AND CONTROL STATES

Variable	Treated States		Control States	
	Mean	**SD**	**Mean**	**SD**
Share of Women Workers	0.059	0.154	0.135	0.248
Daily Wages (in ₹)	398.109	1868.295	347.088	1079.28
Fixed Assets (in ₹)	394700000	4366000000	355500000	4820000000
Working Capital (in ₹)	156300000	4896000000	106100000	2896000000
Sales (in ₹)	1241000000	11670000000	998100000	9791000000

Notes: The table presents summary statistics (mean and standard deviation) for outcome variables and control variables for treated and control states. The treated states are Gujarat, Punjab, Maharashtra and Assam. The states used in my analysis are listed in Table A1 in the appendix.

TABLE 2: SUMMARY STATISTICS FOR NIGHT - SHIFT INDUSTRIES AND OTHER INDUSTRIES

Variable	Night - Shift Industries		Other Industries	
	Mean	**SD**	**Mean**	**SD**
Share of Women Workers	0.189	0.282	0.081	0.19
Daily Wages (in ₹)	296.761	636.707	404.908	1611.086
Fixed Assets (in ₹)	194200000	1078000000	442200000	5584000000
Working Capital (in ₹)	75044238	1365000000	140200000	4196000000
Sales (in ₹)	689900000	2468000000	1232000000	12310000000

Notes: The table presents summary statistics (mean and standard deviation) for all the outcome variables and control variables for night – shift and other industries. Night – shift industries refer to textiles, apparel, leather products, food products, and beverages. The industries used in my analysis are listed in Table A2 in the appendix.

Figure 3 illustrates the share of women workers and daily wages across all states in India. There is significant heterogeneity, with South India and Manipur having a significantly higher share of women workers. On the other hand, daily wages are largely similar, except in Maharashtra, Goa, Tamil Nadu, and Jharkhand with higher daily wages.

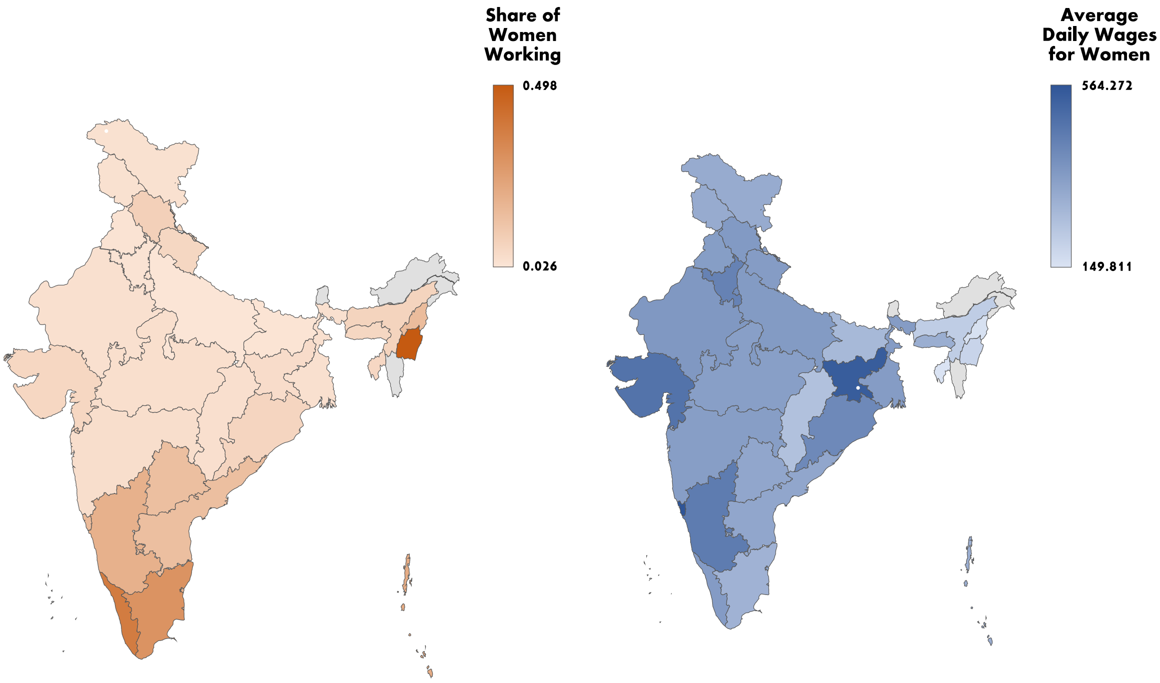


FIGURE 3: MAPS SHOWING SHARE OF WOMEN WORKERS AND DAILY WAGES (IN ₹) ACROSS STATES

Notes: The figure illustrates the share of women workers and daily wages (in ₹) across states in India in a map. Andhra Pradesh and Telangana are shown as separate states in the map, though I consider them as one state (as was the case before 2014) in my analysis. Similarly, Jammu & Kashmir and Ladakh are shown separately, based on the constitutional amendment in 2019, but I consider them as a single state. There is no data on the share of women workers or daily wages for Arunachal Pradesh, Sikkim, and Mizoram, and therefore these are not shaded in the map.

5. Identification Strategy

The relationship between night – shift restrictions and female labour market outcomes is likely to be endogenous. Therefore, the exogenous policy change leads to some states being exposed to unrestricted shifts, with others continuing with night – shift restrictions which provides a natural experiment to estimate the effect of lifting these restrictions on female labour market outcomes.

Considering the nature of this natural experiment, a difference – in – differences strategy could be a potential identification strategy with the counterfactual being other states in India where this policy was not adopted or was adopted before the time period of the study (in this case TN), which would reflect how the treated states would have evolved if the night – shift restrictions were not removed. However, this approach does not eliminate all confounders as different states are likely to be subject to different shocks. This, in turn, could lead to different industry specific trends in the share of women workers and daily wages.

I eliminate industry specific trends by identifying industries which could be affected by the repeal of night – shift restrictions. Unfortunately, I do not have a well – defined set of industries in the literature which require women working at night. Therefore, I rely on context – specific literature and information on the natural experiment itself to identify potentially treated industries.

There is adequate evidence on which industries traditionally employ and rely on women workers in India. Chattapodhyay et al. (2013) and Mondal et al. (2018) show that women have traditionally been employed only in a small sub-set of industries within the manufacturing sector such as textiles, apparel, leather, tobacco, food products, and chemical products. Furthermore, any increases in the employment of women in manufacturing in the past have also been due to increases in employment in the same sub-set of industries. Therefore, any changes in female labour market outcomes due to lifting the night – shift restriction are likely to be in these industries. However, not all of them are likely to employ women during night – shifts. Since I do not have any literature to identify these, I go back to the court proceedings that took place in Gujarat and Tamil Nadu. I find that in the case of Tamil Nadu, it was a worker in a textile factory that filed a petition in the High Court. Furthermore, court proceedings from the case indicate that several petitions were filed by textile manufacturers in the past to lift this restriction. Similarly, in the case of Gujarat, a food processing firm petitioned the court to remove this restriction. Thus, these industries are likely to respond more strongly to the restriction being lifted. I then use the NIC used by our dataset to identify industries that can either be directly or closely classified under the broad categories of textiles and food processing. To this end, I identify 5 industries under the NIC which could potentially be treated, namely, textiles, food products, apparel, leather products and beverages, which I refer to as night – shift industries.

My main empirical strategy is a triple difference model. I begin by estimating Difference – in – Differences models for night – shift industries and other industries. The specifications are detailed below.

$$y^1_{st} = \alpha^1 + \beta^1 Policy_{st} + \gamma_s + \delta_t + \beta X' + \epsilon_{st} \quad (1)$$

Where y^1_{ist} is the value of the outcome variable (either *share of women working* or *log (1 + daily wages*) for night – shift industries, namely textiles, food products, beverages, apparel and leather products in state *s* and year *t*. $Policy_{st}$ is a dummy that takes the value 1 if state *s* (in this case Gujarat, Punjab Maharashtra, and Assam) lifted the restriction in year *t,* and 0 otherwise. γ_s is a set of fixed effects for states and δ_t is a set of fixed effects for years and X' is a vector of controls as described in Section 4.

$$y^0_{st} = \alpha^0 + \beta^0 Policy_{st} + \gamma_s + \delta_t + \beta X' + \epsilon_{ist} \quad (2)$$

Where y^0_{ist} is the value of the outcome variable (either *share of women working* or *log (1+ daily wages*) for non – night shift industries, in state *s* and year *t*. The definitions for all other variables remain the same.

The triple difference equation would simply yield the difference of the DDs estimated in (1) and (2). The triple difference model I estimate is specified as follows:

$$y_{ist} = \beta_0 + \beta_1 Policy_{st} \times NightShift_i + \beta_2 Policy_{st} + \gamma_{s,N} + \delta_{t,N} + \beta X' + \epsilon_{ist} \quad (3)$$

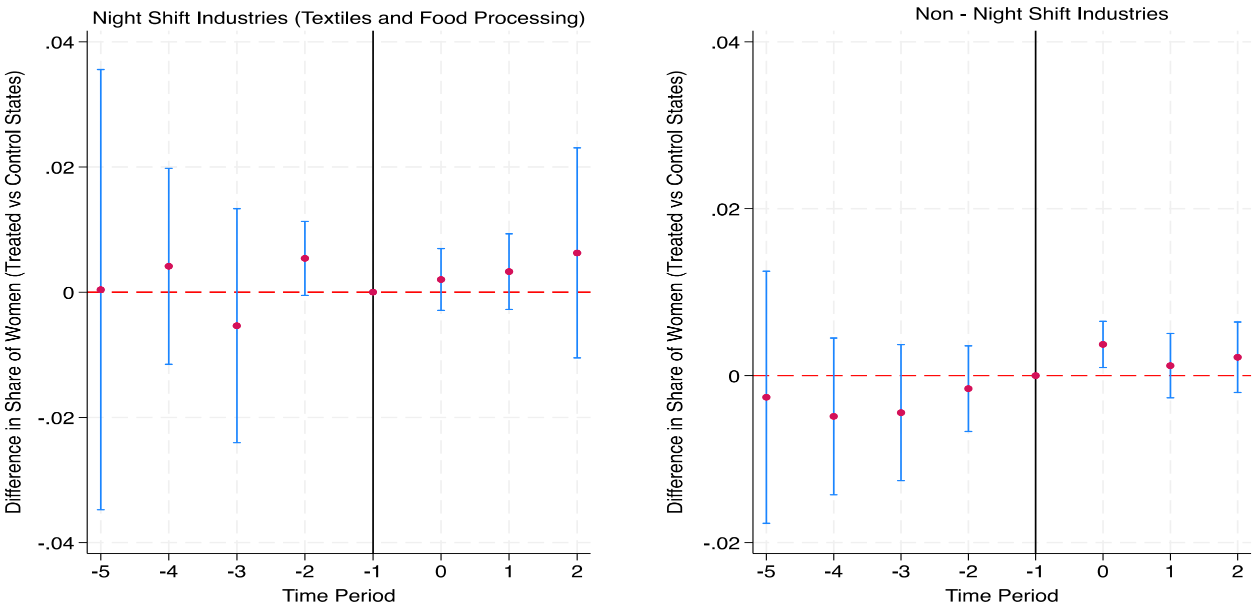
Where y_{ist} is the value of the outcome variable (either *share of women working* or *log (1+ daily wages*), $NightShift_i$ is a dummy variable and takes the value 1 if *`i'* is a night shift industry and 0 otherwise. $\gamma_{s,N}$ is a set of fixed effects for $State \times NightShift$ and $\delta_{t,N}$ is a set of fixed effects for $Year \times NightShift$. Definitions for other variables remain the same. My coefficient of interest is β_1, which captures the Average Treatment Effect on the Treated (ATT), in this case the average treatment effect on night – shift industries.

As with difference – in – differences estimations, I cluster standard errors by state, as in this case, the policy varies by state, in order to account for correlated error terms within states, and the same strategy is applicable to the triple difference model.

Identifying Assumptions: Parallel Trends

The fundamental identifying assumption for a DD estimation is that in the absence of restriction being lifted, states which lifted the restriction and states which did not lift the restriction (or those which lifted the restriction before 2008) would have followed parallel trends. As mentioned above, the triple difference is the difference of 2 DDs, but a valid triple difference estimation does not require parallel trends for both DDs to be satisfied. However, it provides strong evidence that the parallel trends will hold for equation (3) and therefore the estimates would capture the ATT accurately. I first verify that parallel trends hold for equations (1) and (2) by estimating event studies as shown in Figure 4. All standard errors are clustered by state, and I only consider time periods for which I observe all the treated and control states.

Panel A: Event Studies for Share of Women Workers



Panel B: Event Studies for Daily Wages

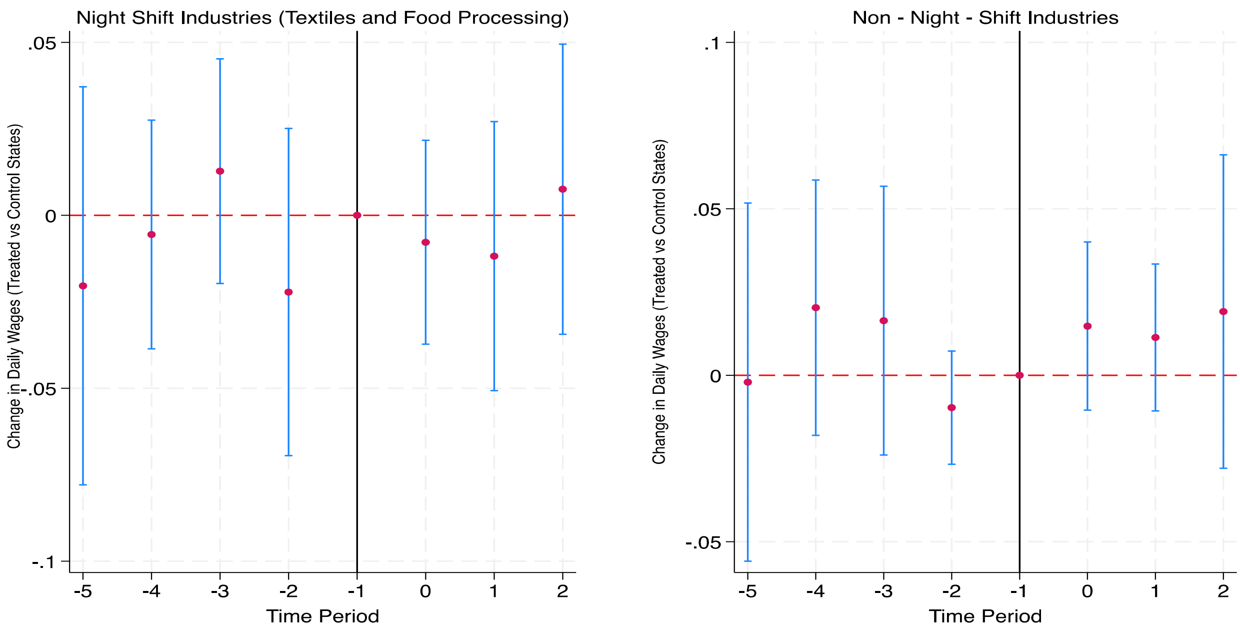


FIGURE 4: EVENT STUDIES FOR DIFFERENCE - IN - DIFFERENCES

Notes: The figure shows the evolution of the share of women workers and daily wages in treated states relative to control states in the form of event studies. All the figures show event study estimates along with the 95% Confidence Intervals. Panel A shows event studies for the share of women workers, first in night – shift industries, and in non – night shift industries. Panel B shows event study estimates for ln(1+daily wages), first in night – shift industries, and in non – night – shift industries. All the event study estimates include controls for state and year fixed effects. Standard Errors are clustered by state.

The event studies suggest that the evolution of the share of women workers and log (1+ daily wages) in the treated and control states follow parallel trends for both night – shift industries as well as non – night shift industries. Furthermore, the non – night shift industries should not experience any statistically significant effects since they are the counterfactual for the night – shift industries which are treated. I only see a very small statistically significant increase in the share of women workers in the other industries at time period 0, and the other periods are close to 0 and statistically insignificant. For wages, all the post – treatment periods are small and statistically insignificant, and therefore my counterfactual for night – shift industries is valid.

I now estimate the triple difference event studies shown in Figure 5. All standard errors are clustered by state, and I only consider time periods for which I observe all treated and control states.

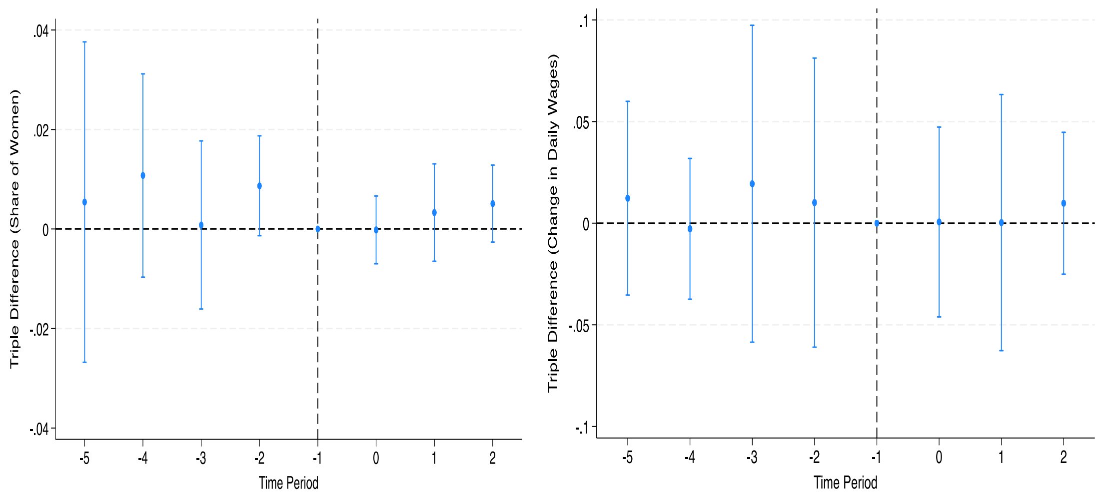


FIGURE 5: EVENT STUDIES FOR TRIPLE DIFFERENCE

Notes: The figure shows event study estimates for the effect of lifting the night – shift restriction on night – shift industries relative to other industries in treated states. The first graph reports the estimates for the share of women workers and the second reports estimates for log(1+daily wages). All estimates are reported along with the 95% confidence interval. All the event study estimates include controls for State × NightShift and Year × NightShift. Standard errors are clustered by state.

Confirming the results from my event studies in Figure 4, I observe that the parallel trends hold for the triple difference as well, and therefore the states and industries I have identified as counterfactuals are valid for a triple difference estimation.

6. Results

6.1 Effect on Share of Women Workers

TABLE 3: DD AND TRIPLE DIFFERENCE ESTIMATES (WITHOUT CONTROLS)

Outcome: Share of Women Workers	**(1)** **DD for Night Shift Industries**	**(2)** **DD for Non - Night Shift Industries**	**(3)** **Triple Difference**
Policy × NightShift			**0.000783**
			[0.00438]
Policy	0.00693	0.00614	0.00614
	[0.00745]	[0.00507]	[0.00507]
Constant	0.188***	0.0800***	0.113***
	[0.000855]	[0.000736]	[0.000741]
Controls	No	No	No
State × NightShift FE	No	No	Yes
Year × NightShift FE	No	No	Yes
State FE	Yes	Yes	No
Year FE	Yes	Yes	No
Observations	120,546	275,129	395,675

Notes: The table reports the effect of lifting the night – shift restriction on the share of women workers. Column (1) reports the effect for the sample of night – shift industries and Column (2) reports the effect on the sample of non – night shift industries. Column (3) reports the triple difference, that is the effect on night – shift industries relative to the other industries in the states which lifted the restriction. I do not include any controls. Standard errors are clustered by state. P – values are coded as follows: *** p<0.01, ** p<0.05, *p<0.1

TABLE 4: DD AND TRIPLE DIFFERENCE ESTIMATES (WITH CONTROLS)

Outcome: Share of Women Workers	(1) DD for Night Shift Industries	(2) DD for Non - Night Shift Industries	(3) Triple Difference
Policy × NightShift			**0.000869**
			[0.00440]
Policy	0.00723	0.00611	0.00610
	[0.00733]	[0.00505]	[0.00505]
Constant	0.190***	0.0805***	0.113***
	[0.00143]	[0.000660]	[0.000688]
Controls	Yes	Yes	Yes
State × NightShift	No	No	Yes
Year × NightShift	No	No	Yes
State FE	Yes	Yes	No
Year FE	Yes	Yes	No
Observations	120,546	275,129	395,675

Notes: The table reports the effect of lifting the night – shift restriction on the share of women workers. Column (1) reports the effect for the sample of night – shift industries and Column (2) reports the effect on the sample of non – night shift industries. Column (3) reports the triple difference, that is the effect on night – shift industries relative to the other industries in the states which lifted the restriction. I also include the closing value of fixed assets, working capital and total sales as controls. Standard errors are clustered by state. P – values are coded as follows: *** p<0.01, ** p<0.05, *p<0.1.

I begin by estimating the effect of lifting the night – shift restriction on the share of women workers. First, I estimate the DD equations (1) and (2) without controls. The estimates are reported in columns 1 and 2 of Table 3 respectively. I find that the share of women working increased by 0.7 p.p in the case of night – shift industries and 0.6 p.p in the case of other industries in the treated states. I then proceed to estimate the triple difference as specified in equation (3). Results of the triple difference estimation are reported in column 3, which yields the difference between the coefficients in columns 1 and 2. I find that the coefficient on *Policy* × *NightShift* (i.e., the average effect on night – shift industries relative to other industries in treated states) is close to 0 and statistically insignificant. The standard errors are relatively small indicating that the estimates are precise. I can rule out effects larger than 0.95 p.p (equivalent to effects larger than 8.4%) on the share of women workers.

In Table 4, I estimate equations (1), (2) and (3), with the controls previously mentioned. The estimates for the DDs are reported in column 1 and column 2, while the estimates for equation (3) are reported in column 3. The estimates remain largely the same, with the coefficient on *Policy* × *NightShift* being close to 0, with small standard errors, and the estimate continues to be statistically insignificant. With effects close to 0 and relatively small standard errors, I can conclude that the policy was ineffective in increasing the share of women workers.

6.2 Effect on Daily Wages

TABLE 5: DD AND TRIPLE DIFFERENCE ESTIMATES (WITHOUT CONTROLS)

Outcome: Log (1+ Daily Wages)	**(1)** **DD for Night Shift Industries**	**(2)** **DD for Non - Night Shift Industries**	**(3)** **Triple Difference**
Policy × NightShift			**0.000942**
			[0.0139]
Policy	**-0.00790**	**-0.00884**	-0.00884
	[0.0216]	**[0.0170]**	[0.0170]
Constant	5.484***	5.643***	5.573***
	[0.00188]	[0.00200]	[0.00183]
Controls	No	No	No
State × NightShift FE	No	No	Yes
Year × NightShift FE	No	No	Yes
State FE	Yes	Yes	No
Year FE	Yes	Yes	No
Observations	55,340	70,740	126,080

Notes: The table reports the effect of lifting the night – shift restriction on daily wages. The outcome variable I use is log (1+daily wages), in order to capture the growth in daily wages. Column (1) reports the effect for the sample of night – shift industries and Column (2) reports the effect on the sample of non – night shift industries. Column (3) reports the triple difference, that is the effect on night – shift industries relative to the other industries in the states which lifted the restriction. I do not include any controls in my regressions. Standard errors are clustered by state. P – values are coded as follows: *** p<0.01, ** p<0.05, *p<0.1

TABLE 6: DD AND TRIPLE DIFFERENCE ESTIMATES (WITH CONTROLS)

Outcome: Log (1 + Daily Wages)	**(1)** **DD for Night Shift Industries**	**(2)** **DD for Non - Night Shift Industries**	**(3)** **Triple Difference**
Policy × NightShift			**0.00122**
			[0.0142]
Policy	**-0.00828**	**-0.00954**	-0.00964
	[0.0209]	**[0.0165]**	[0.0164]
Constant	5.469***	5.628***	5.562***
	[0.00629]	[0.00231]	[0.00197]
Controls	Yes	Yes	Yes
State × NightShift FE	No	No	Yes
Year × NightShift FE	No	No	Yes
State FE	Yes	Yes	No
Year FE	Yes	Yes	No
Observations	55,340	70,740	126,080

Notes: The table reports the effect of lifting the night – shift restriction on daily wages. The outcome variable I use is log (1+daily wages), in order to capture the growth in daily wages. Column (1) reports the effect for the sample of night – shift industries and Column (2) reports the effect on the sample of non – night shift industries. Column (3) reports the triple difference, that is the effect on night – shift industries relative to the other industries in the states which lifted the restriction. I also include the closing value of fixed assets, working capital and sales as controls. Standard errors are clustered by state. P – values are coded as follows: *** p<0.01, ** p<0.05, *p<0.1

Now, I estimate the effect of lifting the night – shift restriction on daily wages. First, I estimate the DD equations (1) and (2) without controls, and the outcome variable is log(1+daily wages). The estimates are reported in columns 1 and 2 of Table 5 respectively. I find that the daily wages of women workers decreased by 0.8% in the case of night – shift industries and 0.88% in the case of other industries in states which lifted the restriction. I then estimate the triple difference model, as specified in equation (3). Results of the triple difference estimation are reported in column 3 of Table 5, which yields the difference between the coefficients in columns 1 and 2. The coefficient for $Policy \times NightShift$ is close to 0, and statistically insignificant, i.e., daily wages for night – shift industries did not change relative to other industries in the treated states. The estimates have relatively small standard errors indicating that the estimates are precise. I can also rule out effects larger than 2.8%.

In Table 6, I estimate equations (1), (2) and (3) for log(1+daily wages) with the controls previously mentioned. The estimates for the DDs are reported in column 1 and column 2 of Table 6, while the estimates for equation (3) are reported in column 3. The estimates remain nearly the same, with the effect being close to 0, with small standard errors, and the estimate continues to be statistically insignificant. With effects close to 0 and relatively small standard errors, I can conclude that the policy was ineffective in terms of increasing the wages of women workers.

7. Threats to Validity and Robustness Checks

7.1 Small Number of Clusters

In line with conventional literature, as the night – shift restrictions vary by state, I cluster standard errors by state to account for within – state dependence of error terms. However, standard asymptotic properties do not hold when the number of clusters are small (less than 50), and therefore inferences based on standard test statistics are invalid (Bertrand et al., 2004). Since I have only 31 states, I perform a wild cluster bootstrap as recommended in Cameron et al. (2008). First, I use the specification mentioned in equation (3), with the outcome variable being share of women workers, and estimate p – values and confidence intervals for my main coefficient of interest β_1 using a wild cluster bootstrap and results for the estimates are reported in Table 7

TABLE 7: WILD CLUSTER BOOTSTRAP FOR SHARE OF WOMEN WORKERS

Outcome: Share of Women Workers	Estimate	P - Value	Confidence Interval
Policy × NightShift	**0.00078**	**0.892**	**[-0.009, 0.0116]**
Policy	0.006	0.249	[-0.004, 0.023]

Notes: The table reports the p – values and Confidence intervals for my triple difference estimate for the share of women workers from equation (3) using a wild cluster bootstrap. I report the coefficients for Policy × NightShift and Policy, though my coefficient of interest is the former, which yields the triple difference.

The results suggest that my estimated ATT is statistically insignificant corroborating my inference from estimates in Tables 3 and Tables 4, and the confidence intervals are also similar, indicating that my cluster - based inference is robust despite having fewer than 50 clusters.

I now proceed to estimate equation (3), with the outcome variable being log (1+daily wages) and estimate p- values and confidence intervals for β_1. The estimates are reported in Table 8.

TABLE 8: WILD CLUSTER BOOTSTRAP FOR LOG(1+DAILY WAGES)

Outcome: Log(1+daily wages)	**Estimate**	**P - Value**	**Confidence Interval**
Policy × NightShift	**0.00094**	**0.95**	**[-0.036, 0.036]**
Policy	-0.0088	0.612	[-0.07, 0.025]

Notes: The table reports the P – values and Confidence intervals for my triple difference estimate for log(1+daily wages) from equation (3) using a wild cluster bootstrap. I report the coefficients for Policy × NightShift and Policy, though my coefficient of interest is the former, which yields the triple difference.

As with the share of women workers, the wild cluster bootstrap suggests that my estimated ATT is indeed statistically insignificant, thereby corroborating the results obtained in Tables 5 and 6, and the confidence intervals are also similar. Therefore, my inference is robust in this case as well.

7.2 Biased Treatment Effects due to Staggered Adoption

Recent literature on Difference – in - Differences has pointed out that treatment effects estimated in a staggered setting may be biased. One, the canonical two – way fixed effects model estimates treatment effects by comparing treated and already – treated units. If there are dynamics, where the treatment effect changes over – time for the already-treated units, they may not serve as a valid counterfactual, thereby biasing my estimates. Two, the weights assigned can be negative, and groups treated at the middle of the treatment period are assigned higher weights, which could also bias estimates (Goodman – Bacon, 2021).

Since states lift the night – shift restriction in consecutive years starting from 2013 to 2016, my model estimates treatment effects for instance, by comparing industries in Maharashtra (treated in 2015) with industries in Gujarat (treated in 2013), and similarly with other already - treated units. Furthermore, I might also have states treated in 2014 or 2015, being assigned higher weights. These could bias my estimates, in addition, to the fact that dynamics in already – treated states might make my counterfactual invalid.

In general, these treatment effects are likely to be biased only if a large number of states are treated. In my case, I have only 4 states adopting the policy, and 27 not being treated at all. Nevertheless, I verify the robustness of my results to the problems discussed above by using a stacked triple difference in line with Cengiz et al. (2019) and Deshpande and Li (2019). To begin with, I identify an event window, wherein all states have the same number of pre – treatment and post – treatment periods. In my case, Gujarat is the first state to be treated and has only 5 years of pre – treatment observations. Furthermore, Assam is the last state to adopt the policy in 2016 and has only observations for 3 post – treatment periods (including the year of adoption). Therefore, I define an event window of 8 years, thereby ensuring that all states have atleast 5 pre – treatment and 3 post – treatment periods. This ensures that all the states are assigned equal weights, and therefore removes bias due to arbitrary weighting of treated units.

Next, I create separate datasets (or stacks) for each state that adopted the policy (i.e., stacks for Gujarat, Punjab, Maharashtra, and Assam each) keeping observations only within the 8-year window. In each stack, I only keep clean controls, i.e., observations for states which were not treated in the 8-year period. For Gujarat, this includes all states except Punjab and Maharashtra. For all other treated states, I exclude any other state treated during the entire period of my study, as they would be treated in the 8-year window. I generate a stack indicator variable, $Stack_d$ for each stack *d* such that $Stack_d = \{d \mid d = (1,2,3,4)\}$. In each stack, I also create a dummy $Policy_{std}$ for each stack d, which takes the value 1 if state *s* is treated in year *t* and 0 for clean controls. This eliminates any potential bias arising out of comparisons between treated and already – treated units.

I then append all stacks to create a consolidated stacked dataset. I first proceed to estimate a stacked event study, as specified below.

$$\begin{aligned} y_{isdt} = \beta_0 &+ \sum_{\tau=-5}^{2} \beta_\tau \times \mathbf{1}(TimePeriod_{td} = \tau) \\ &+ \sum_{\tau=-5}^{2} \beta_\tau \times Treat_{sd} \times NightShift_i \times \mathbf{1}(TimePeriod_{td} = \tau) + \boldsymbol{Z_{s,N,d}} \\ &+ \boldsymbol{\delta_{t,N,d}} + \epsilon_{isdt} \qquad (4) \end{aligned}$$

Where, y_{isdt} is the value of the outcome variable (either share of women workers or log(1+daily wages)) in industry *'i'* in state *s* belonging to stack d and in the year *t*. $Treat_{sd}$ is a dummy which takes the value 1 if a state *s* is treated in stack *d* and 0 otherwise.

$TimePeriod_{td} = year_t - event_d$, where $event_d$ takes the value of the year when the night – shift restriction was lifted in the treated state in each stack *d*. $\mathbf{1}(TimePeriod_{td} = \tau)$ is a set of dummies for each time period τ, which take the value of 1 when $(TimePeriod_{td} = \tau)$, and 0 otherwise. The definitions of other variables remain unchanged. $\boldsymbol{Z_{s,N,d}}$ is a set of fixed effects for State × NightShift × Stack and $\boldsymbol{\delta_{t,N,d}}$ is a set of fixed effects for Year × NightShift × Stack. The estimates are presented in Figure 6.

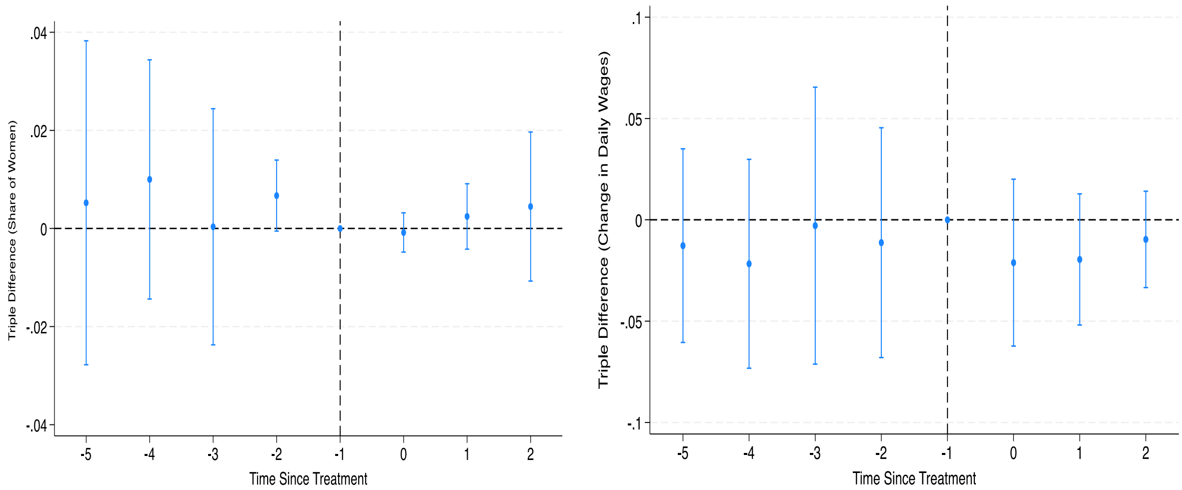


FIGURE 6: STACKED EVENT STUDIES

Notes: The figure shows stacked event study estimates for the effect of lifting the night – shift restriction on night – shift industries relative to the other industries in states which adopted the policy. The first graph reports the estimates for the share of women workers and the second reports estimates for log(1+daily wages). All estimates are reported along with the 95% confidence interval. All the event study estimates include controls for State × NightShift × Stack and Year × NightShift × Stack. Standard errors are clustered by state.

Firstly, parallel trends hold for both outcome variables in the pre – treatment periods, and furthermore, I also see small and insignificant changes in the share of women workers and wages after the restriction was lifted. In order to confirm these results, I proceed to estimate a stacked triple difference model, which is specified below:

$$y_{isdt} = \beta_0 + \beta_1 Policy_{std} \times NightShift_i + \beta_2 Policy_{std} + \beta X' + \boldsymbol{Z_{s,N,d}} + \boldsymbol{\delta_{t,N,d}} + \epsilon_{isdt} \quad (5)$$

Where y_{isdt} is the value of the outcome variable in industry i in state *s* in year *t* in stack *d*. $Policy_{std}$ is a dummy as defined previously. Definitions for other variables remain the same.

There are 2 different approaches that are taken with stacked DDs in existing literature with respect to clustering standard errors. While Cengiz et al. (2019) cluster by Unit × Stack, Deshpande and Li (2019) cluster by Unit. However, I use the latter as clustering by Unit × Stack is prone to over – rejection as shown by Wing (2021).

TABLE 9: STACKED TRIPLE DIFFERENCE ESTIMATES

	(1)	(2)	(3)	(4)
Outcome	Share of Women	Log (1+ daily wages)	Share of Women	Log (1+ daily wages)
Policy × NightShift	**-0.00233**	**-0.00687**	**-0.00226**	**-0.00503**
	[0.00420]	**[0.0137]**	**[0.00420]**	**[0.0132]**
Policy	0.00530	0.00852	0.00526	0.00638
	[0.00438]	[0.0146]	[0.00436]	[0.0141]
Constant	0.125***	5.550***	0.126***	5.539***
	[0.000245]	[0.000595]	[0.000225]	[0.00154]
State × Stack × Night Shift	Yes	Yes	Yes	Yes
Year × Stack × Night Shift	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Observations	947,847	319,278	947,847	319,278

Notes: The table reports the effect of lifting the night – shift restriction on the share of women workers and daily wages using a stacked triple differences estimation. For daily wages, I use the log (1+daily wages) as the outcome variable in order to estimate the change in daily wages. Columns (1) and (2) report estimates without controls. Columns (3) and (4) report estimates where I include controls for the closing value of fixed assets, working capital and total sales. Standard errors are clustered by state. P – values are coded as follows: *** p<0.01, ** p<0.05, *p<0.1.

I first estimate equation (5) for both share of women workers and log(1+daily wages) without controls, and the results reported in columns 1 and 2 of Table 9 respectively. Though I obtain a negative coefficient for β_1, they continue to be very small and statistically insignificant, with standard errors equivalent to the ones I obtained in my estimates of equation (3). I am also able to rule out effects larger than 0.59 p.p (equivalent to effects larger than 4.7%) in the share of women workers, and effects larger than 2% for daily wages. These effects are again very similar to those obtained in tables 5 and 6.

Columns 3 and 4 report my estimates for equation (6) for the share of women workers and log(1+daily wages) respectively with controls. The results obtained are similar to those reported in columns 1 and 2. Therefore, my estimates from the triple difference are valid, and I continue to find that lifting the night – shift restriction had no significant impact and the estimated treatment effects are robust to the issues outlined previously.

7.3 Alternative Control Groups

The fundamental identifying assumption for choosing a valid counterfactual in my triple difference, is that in the absence of the treatment, the outcome in night – shift industries relative to other industries would have followed parallel trends in the treated and control states. This alone is necessary and sufficient for my counterfactual to be valid. However, Tables 1 and 2 suggest that the share of women workers in the treated states are less than half of that in the control states, while the night – shift industries have more than double the share of women workers as compared to other industries. If there are significant level – differences, perhaps the 2 groups of states or industries have different fundamental characteristics which could potentially lead to them evolving differently, thereby making my counterfactual and estimates invalid. It is therefore useful to verify that my results are not influenced by these level differences, by choosing alternative groups at similar levels.

To begin with, I fix thresholds for both control states as well as the non – night – shift industries to qualify as a counterfactual based on the levels before 2013, as none of the states had adopted the policy during that period. The pre – 2013 means for the state and industry groups are reported in Table 10.

TABLE 10: SHARE OF WOMEN WORKERS (PRE - 2013)

Outcome	Mean Share of Women
Night Shift Industries	0.176
Non - Night Shift Industries	0.081
Treated States	0.053
Control States	0.133

Notes: The table provides the mean share of women workers before 2013 (i.e., before the night – shift restrictions were lifted by any state) in the treated and control states, and in night – shift and non – night shift industries. The treated states comprise of Punjab, Gujarat, Maharashtra, and Assam, and night – shift industries refer to textiles, apparel, leather products, food products, and beverages.

For a non – night shift industry to be a counterfactual, I define a threshold of 4.5% (approximately, 25% of the mean of night – shift industries). Any industry with a mean share of women workers below this threshold will be excluded. For control states to be a valid counterfactual, I define a threshold of 20% (approximately 4 times the mean of the treated states). Any state with a mean share of women workers above the threshold will be excluded from the control group.

Table 11 presents summary statistics after excluding industries and states that do not meet the threshold criterion.

TABLE 11: SHARE OF WOMEN WORKERS (AFTER IMPOSING THRESHOLD)

Outcome	Mean Share of Women
Night Shift Industries	0.08
Non - Night Shift Industries	0.07
Treated States	0.07
Control States	0.08

Notes: The table provides the mean share of women workers before 2013 (i.e., before the night – shift restrictions were lifted by any state) in the treated and control states, and in night – shift and non – night shift industries. Note that the control states here are only those whose share of women workers is less than 20% before 2013. Similarly, non – night shift industries are only those industries whose share of women workers is greater than 4.5%. The treated states comprise of Punjab, Gujarat, Maharashtra, and Assam, and night – shift industries refer to textiles, apparel, leather products, food products, and beverages.

Now, I obtain groups which are similar in levels. With these industries and states, I estimate equation (3), and the results are reported in Table 12.

TABLE 12: TRIPLE DIFFERENCE ESTIMATES USING ALTERNATIVE CONTROL GROUP

Outcome: Share of Women Workers	(1)	(2)
Policy × NightShift	**0.000511**	**0.000459**
	[0.00634]	**[0.00635]**
Policy	-0.000508	-0.000362
	[0.00431]	[0.00430]
Constant	0.0816***	0.0826***
	[0.000772]	[0.000978]
Controls	No	Yes
State × NightShift FE	Yes	Yes
Year × NightShift FE	Yes	Yes
Observations	220,270	220,270

Notes: The table reports the triple difference estimates using the alternative state and industry control groups. A state is included in the control group if the share of women working before 2013 is < 20% and an industry is a control industry (or a non – night shift industry) if the share of women working is > 4.5% before 2013. Column (1) reports estimates without controls. Column (2) reports estimates where I include controls for the closing value of fixed assets, working capital and total sales. Standard errors are clustered by state. P – values are coded as follows: *** p<0.01, ** p<0.05, *p<0.1.

Column 1 presents estimates without controls, and column 2 with controls. These results are consistent with results obtained in Tables 3 and 4 when considering the full set of states and industries. I continue to find very small and statistically significant treatment effects, and I am able rule out effects larger than 1.3 p.p., which are similar to those obtained previously. Therefore, I can conclude that my results are robust to the use of alternative control groups at similar levels.

7.4 Synthetic Control Method

I use the synthetic control method for multiple treated units and multiple time periods in line with Cavallo et al., (2013), to estimate the effects of lifting the night – shift restriction on night – shift industries. I find that my results are robust under this method, with no significant effects on the share of women workers or daily wages. The details and results are presented in Appendix B.

8. Conclusion

In this paper, I look at the effect of removing restrictions on night – shifts for women workers in manufacturing on their labour market outcomes. Using a natural experiment in India, where 4 states (Gujarat, Punjab, Maharashtra, and Assam) lifted the restriction in the Factories Act prohibiting women from working in night shifts, I employ a triple difference strategy to estimate the effect of lifting the restriction on the share of women workers and daily wages, in night – shift industries.

The results suggest that lifting the restriction was ineffective, as I find that the effects on the share of women workers as well as daily wages are close to 0 and statistically insignificant, but with small standard errors indicating that my estimates are relatively precise. These results are robust to the use of Stacked Triple Differences, Wild Cluster Bootstrap inference, and other robustness checks.

Previous case – studies provide several possible explanations for my results. One, with the violation of safety measures seen in Tamil Nadu, this could potentially be the case with other states, and therefore could be one of the reasons I see no effect of on the share of women workers. Furthermore, the TN case study also suggests that to build a safe environment for women workers would require deliberations with the various stakeholders involved, and factories have to set up the required infrastructure such as transportation facilities and adequate security which would require investments. This means factories may simply not employ women workers in night - shifts to avoid such investments, or if they do the effects are likely to be seen in the medium to long – term. This could explain why I do not see an increase in wages, as even existing women workers are possibly not employed in night – shifts with higher wages. Furthermore, like with call centres, the social perception becomes positive towards night – work for women gradually. With the services sector where women workers are educated (either with a high – school certificate or a Bachelors' degree) and largely urban, manufacturing workers are often low – skilled and are in the lower – end of the education distribution (Gupta, 2021) (Klasen & Pieters, 2015). This would mean that the social strata of the two types of workers are significantly different, and therefore this perception change is likely to be slow, if not slower for manufacturing workers.

This paper has several important policy implications given that more states such as Andhra Pradesh, Telangana, Karnataka, and Goa have lifted the night – shift restrictions since 2020[5], and the central government in the new labour codes has also proposed to lift the restriction across the country. While this paper is not an argument to continue the restriction on night – shifts, the results provide important lessons for all the state governments and the central government. One, policymakers should not overestimate gains to female labour market outcomes owing to lifting this restriction alone and should combine this with policies on creating awareness about job opportunities for women and skill – training, which have proven to be very effective in improving female labour market outcomes among rural as well as low-skilled workers (Jensen, 2012) (Mehrotra & Parida, 2017). Two, governments need to be more proactive in creating and enforcing safety norms, while also incentivising factories to invest in the requisite safety infrastructure.

My study suffers from some limitations. One, there is no publicly available data on shifts being worked by women workers. As a result, I could not determine whether this policy led to an increase in women working at night, without wage incentives. Though this does not undermine my conclusions in any way and the motivation for the paper holds, it would have provided additional evidence to back my conclusions. Two, the ASI being repeated cross - sections, meant that I could not examine the effect of allowing night – shifts at the firm - level.

[5] These states could not be included in my analysis owing to the lack of availability of ASI data after 2019.

One, this would provide more variation and therefore more precise estimates. Furthermore, shifts are likely to vary vastly across firms and estimating impacts at the firm level would be useful in validating my estimates at the industry-level. Furthermore, there is likely to be heterogenous effects across different types of firms, which again would be useful to examine using a firm – level dataset.

Through my results, I have established that the policy was ineffective, and I have some supportive evidence of why it may not have improved labour market outcomes, based on existing literature and case studies. However, I do not have data or qualitative evidence on why it did not work in the specific states I considered. This would require either an RCT or primary data collection, which is beyond the scope of this paper. Nevertheless, this would provide additional evidence on mechanisms that drive my results. This could be an object of study for further research.

Bibliography

Acemoglu, D., Autor, D. H., & Lyle, D. S. (2004). Women, War, and Wages: The effect of female labor supply on the wage structure at Midcentury. *Journal of Political Economy*, *112*(3), 497–551. https://doi.org/10.1086/383100

Aggarwal, A. (2012). *Social and economic impact of SEZs in India*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780198077275.001.0001

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust Differences-In-Differences Estimates? *Quarterly Journal of Economics*, *119*(1), 249–275. https://doi.org/10.1162/003355304772839588

Bhalla, S. and Kaur, R. (2011) *Labour force participation of women in India: some facts, some queries.* Working Paper (40). Asia Research Centre, London School of Economics and Political Science, London, UK. https://eprints.lse.ac.uk/38367/

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-Based Improvements for Inference with Clustered Errors. *The Review of Economics and Statistics*, *90*(3), 414–427. https://doi.org/10.1162/rest.90.3.414

Cavallo, E. A., Galiani, S., Noy, I., & Pantano, J. (2013). Catastrophic natural disasters and economic growth. *The Review of Economics and Statistics*, *95*(5), 1549–1561. https://doi.org/10.1162/rest_a_00413

Cengiz, D., Dube, A., Lindner, A., & Zipperer, B. (2019). The effect of minimum wages on Low-Wage jobs. *Quarterly Journal of Economics*, *134*(3), 1405–1454. https://doi.org/10.1093/qje/qjz014

Chattopadhyay, M., Chakraborty, S., & Anker, R. (2013). Sex segregation in India's formal manufacturing sector. *International Labour Review*, *152*(1), 43–58. https://doi.org/10.1111/j.1564-913x.2013.00168.x

CSO. (2016). *Annual Survey of Industries 2013-14: Study Documentation* (DDI-IND-CSO-ASI-2013-14). Central Statistics Office (Industrial Wing), Ministry of Statistics and Programme Implementation, Government of India. Retrieved June 19, 2023, from https://microdata.gov.in/nada43/index.php/catalog/26/study-description#page=sampling&tab=study-desc

DeBeaumont, R., & Nsiah, C. (2009). Unemployment and compensating wages: an analysis of shift work. *Journal of Economics and Finance*, *34*(2), 142–149. https://doi.org/10.1007/s12197-009-9093-3

Deshpande, A. & Singh, J. (2021) *Dropping Out, Being Pushed out or Can't Get In? Decoding Declining Labour Force Participation of Indian Women.* IZA Discussion Paper No. 14639. https://www.iza.org/publications/dp/14639/dropping-out-being-pushed-out-or-cant-get-in-decoding-declining-labour-force-participation-of-indian-women

Deshpande, M., & Li, Y. (2019). Who is screened out? Application costs and the targeting of disability programs. *American Economic Journal: Economic Policy*, *11*(4), 213–248. https://doi.org/10.1257/pol.20180076

Galiani, S., & Quistorff, B. (2017). The Synth_Runner Package: Utilities to automate synthetic control estimation using Synth. *Stata Journal*, *17*(4), 834–849. https://doi.org/10.1177/1536867x1801700404

Ganashree, A. (n.d.). *The Factories Act, 1948*. People's Archive of Rural India. Retrieved August 10, 2023, from https://ruralindiaonline.org/en/library/resource/the-factories-act-1948/?gclid=CjwKCAjwloynBhBbEiwAGY25dC6BJsq7aVNCOGkdQZv446qPxovICVzljo_syOVI2Dhuh7hm5adwBhoCRVYQAvD_BwE

Gartenberg, I., & Bandekar, S. (2011). Challenges to ensuring core labour standards in transnational corporations: The case of India. *The Indian Journal of Labour Economics*, *54*(2), 269–284. https://www.researchgate.net/publication/319254044_Challenges_to_ensuring_core_labour_standards_in_transnational_corporations_The_case_of_India

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014

Gothoskar, S. (2006). Gender and Work in the "Digital Economy" [Review of Gender and the Digital Economy: Perspectives from the Developing World, by S. Mitter & Cecilia Ng]. Economic and Political Weekly, 41(16), 1517–1520. http://www.jstor.org/stable/4418108

Gupta, A. (2021). Effect of trade liberalization on gender inequality: The Case of India. *IMF Economic Review*, *69*(4), 682–720. https://doi.org/10.1057/s41308-021-00143-7

Jensen, R. T. (2012). Do Labor Market Opportunities Affect Young Women's Work and Family Decisions? Experimental Evidence from India. *Quarterly Journal of Economics*, *127*(2), 753–792. https://doi.org/10.1093/qje/qjs002

Kato, T., & Kodama, N. (2017). Deregulating Overtime Hours Restrictions on Women and its Effects on Female Employment: Evidence from a Natural Experiment in Japan. *Oxford Bulletin of Economics and Statistics*, *80*(4), 804–821. https://doi.org/10.1111/obes.12221

Klasen, S. & Pieters, P. (2012). *Push or Pull? Drivers of Female Labor Force Participation during India's Economic Boom.* IZA Discussion Paper No. 6395.

https://www.iza.org/publications/dp/6395/push-or-pull-drivers-of-female-labor-force-participation-during-indiaseconomic-boom

Klasen, S., & Pieters, J. (2015). What explains the stagnation of female labor force participation in urban India? *The World Bank Economic Review*, *29*(3), 449–478. https://doi.org/10.1093/wber/lhv003

Kostiuk, P. F. (1990). Compensating differentials for shift work. *Journal of Political Economy*, *98*(5, Part 1), 1054–1075. https://doi.org/10.1086/261719

Mehrotra, S., & Parida, J. K. (2017). Why is the Labour Force Participation of Women Declining in India? *World Development*, *98*, 360–380. https://doi.org/10.1016/j.worlddev.2017.05.003

Narasimhan, T. E., & Sethi, A. (2014, August 11). Women on night shift: A lesson from Tamil Nadu. *Business Standard*. https://www.business-standard.com/article/current-affairs/women-on-night-shift-a-lesson-from-tamil-nadu-114081200027_1.html

Padmanabhan, E. (2000). Vasantha R. vs Union Of India (Uoi) And Ors. In *Indian Kanoon*. Madras High Court. Retrieved September 9, 2023, from https://indiankanoon.org/doc/715470/

Rustagi, P. (2013). Changing Patterns Of Labour Force Participation And Employment Of Women In India. *The Indian Journal of Labour Economics*, *56*(2), 215–241. https://www.researchgate.net/publication/281190519_Changing_patterns_of_labour_force_participation_and_employment_of_women_in_India

Sarkar, S., Sahoo, S., & Klasen, S. (2019). Employment transitions of women in India: A panel analysis. *World Development*, *115*, 291–309. https://doi.org/10.1016/j.worlddev.2018.12.003

Singh, P., & Anu Pandey. (2005). Women in Call Centres. Economic and Political Weekly, 40(7), 684–688. http://www.jstor.org/stable/4416207

Wing, C. (2021). Statistical Inference For Stacked Difference in Differences and Stacked Event Studies. In *Indiana University Workshop in Methods*. Workshop in Methods, Bloomington, Indianapolis, United States of America. https://scholarworks.iu.edu/dspace/handle/2022/26875

Zveglich, J. E., & Van Der Meulen Rodgers, Y. (2003). The impact of protective measures for female workers. *Journal of Labor Economics*, *21*(3), 533–555. https://doi.org/10.1086/374958