The Effect of Compulsory Primary Education on Mothers' Labor Force Participation

Deepika Baskar Prabhakar

India's female labor force participation rates have been steadily declining for the last decade (Mehrotra and Parida 2017). Low female labor force participation is often associated with a reduction in GDP per capita and economic growth (Agénor and Canuto 2015). Thus, as part of a strategy for increasing economic growth, it is necessary to examine factors that could potentially increase female labor force participation. One of the aspects that could increase labor force participation is childcare (Connelly 1992). However, in low-income countries like India, childcare is often expensive and inaccessible. In my thesis, I examine if relaxing this constraint by providing free and compulsory education to children as substitute childcare will encourage higher female labor force participation.

I use tools from classic economic theory to build a household unitary model to illustrate how compulsory primary education will affect labor market decisions. My model predicts that households' labor market decisions are dependent on how the households budget and time constraints are affected in response to children going to school. Since my model yields ambiguous results I use data to test my hypothesis using empirical strategies.

I use data from the Indian National Rural Employment and Unemployment Surveys conducted by the Government. The Right to Education act was passed by the Indian Government that made primary education free and compulsory for all primary students. I explore 3 different empirical strategies that exploit the phased roll-out nature of this policy to test for a causal effect.

I find that the probability of a woman's decision to enter the labor market increases by $1.7\% - 1.8\%$ in some states. However, my results remain statistically insignificant when I include all states in India in my estimation. Thus, other factors such as gender norms, safety for women in the workplace, and wage disparity should be explored to encourage higher female labor force participation in countries like India.

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Introduction

India has one of the world's lowest female labor force participation rates in the world with just 29.2% of women employed or actively looking for work. (Verick 2014). Low female labor force participation is associated with a reduction in GDP per capita and economic growth (Agénor and Canuto 2015). Some of the factors that could potentially explain the low female labor force participation include lack of access to employment, wage disparity, gender discrimination, and the burdens of family responsibilities (Verick 2014). Therefore, it is important to examine policies that would relax these factors and encourage higher female labor force participation to increase economic growth and welfare.

There is a large literature that examines the effects of female labor force participation on welfare factors. In particular, higher female labor force participation has been associated with better health for children, and lesser discrimination towards female children (Bose and Das 2017; Brander and Dowrick 1994). Moreover, higher labor force participation increases women's bargaining power within households, giving them autonomy and lowering the risk of domestic violence(Anderson and Eswaran 2009). Other papers have concentrated on factors that increased labor force participation. Some factors associated with higher labor force participation are childcare facilities and higher school enrollments (Compton and Pollak 2014; Heath 2014).

Past literature has also illustrated that childcare bolsters female labor force participation (Lee and Lee 2014; Connelly 1992). For instance, a study shows that women in a garment factory were 1.71 times higher to be present at work when the company sponsored daycare than when they did not have access to childcare (Ranganathan and Pedulla 2021). However, most of the literature is concentrated in high-income countries so daycare may not necessarily be a solution for women in low-income constraints because of budget constraints. In this thesis, I examine if relaxing a women's childcare constraint by providing free and compulsory primary labor force participation could possibly encourage higher labor force participation. There are no other papers that examine using primary education as substitute childcare to my knowledge. Thus, my work will add to the literature that explores elementary schooling as possible childcare in low-income countries

I examine my hypothesis using the Right to Education Act(RTE) formally passed by the Indian Central Government on 4th August 2009. The individual State Governments in India were then responsible for implementing the act in their respective states making it a phased rollout design from $2010 - 2012$. The act encouraged better access to education for everyone as it increased school children's overall enrollment rates (Shah and Steinberg 2019). My thesis specifically examines how this increase in children's enrollment rate would affect mothers' labor force participation decisions.

I first build a simple theoretical model that examines how different household constraints will affect labor market decisions. Specifically, I construct a unitary household model where the household chooses between how much market goods, household production goods, and leisure to consume with respect to budget and time constraints. My model predicts that a women's labor force participation depends on how the household's budget and time constraint change in response to the policy. Since I have ambiguous results from my theoretical model, I use an empirical model to test labor market decision predictions.

I use household data from the Indian National Employment and Unemployment Surveys for the years 2009 - 2012. These repeated cross-section surveys provide information on each member's primary activity for the day and other demographic characteristics of the household. I use this data and 3 different econometric techniques that exploit the phased implementation of this policy to test for causal effects.

As a first step, I implement a differences-in-differences technique that uses the states where the policy was implemented first as the treatment group and the states where the policy was implemented last as the control group. My results from this model suggest that the probability of a mother entering the labor force increases by $1.7 - 1.8\%$. However, my results may be biased as they suffer from many limitations as my estimates do not include all states of India. As a next step, I use a two-way fixed effects regression with staggered timing. My results show a small transient period with negative effects and then show statistically insignificant results for the rest of the time periods. However, recent literature has highlighted that using a two-way fixed effects regression with staggered timing leads to biased estimates (Goodman-Bacon 2021).

In response to these estimation technique issues, there are many papers that propose different econometric methods (Sun and Abraham 2021; Callaway and SantAnna 2021). For the purpose of my thesis, I use the estimator proposed by Callaway and SantAnna (2021), to test my hypothesis. My results are statistically insignificant under this estimator. My overall results suggest there are some encouraging signs that the RTE increases female labor force participation, however, this cannot be generalized to the whole country. Other factors like equal employment opportunity, changing gender norms, and lesser wage disparity are other potential factors that should also be explored to increase female labor force participation.

The rest of the thesis is arranged as follows: Chapter 2 provides background information, policy description, and an overview of the past literature. Chapter 3 presents the theoretical model, Chapter 4 explains my empirical model, and 5 concludes.

Background

In order to analyze how the Right to Education Act would impact female labor force participation, it is important to provide some background information. I first give additional details of the two policies that are relevant to my analysis. I begin with a detailed description of the Right to Education Act and then discuss the relevant policy that preceded that. Specifically, the SSA provided infrastructure that enabled the RTE to be enforced. I then discuss how my research work fits in with past literature.

2.1 Policy Description

2.1.1 The Right to Education Act

In order to examine the effect of free and compulsory primary education on the children's mother labor force participation, I consider the Right to Education (RTE) Act passed by the Indian Government in August 2009. The law made primary education a fundamental right for each child and that every child between the ages of 6 and 14 should attend school. There were five main provisions for the RTE that were uniform across states. They are listed below:

- Requires 25% of all seats in private schools reserved for children from low-income communities and socially disadvantaged groups
- Prohibits schools not recognized by the government from practice
- Bans admissions through donations/interviews of the child or parent
- Prohibits children from failing a class or getting expelled from school
- Provides special training for school dropouts

This act encourages equitable access to education for everyone, thus increasing the overall enrollment rates for school children (Shah and Steinberg 2019). The Indian government is estimated to have spent approximately USD 38.2 billion for implementing this act. The act also requires surveys to monitor all neighborhoods to identify children who require education and provide for it. The law was passed by the Indian central government, however, the state governments were responsible for implementing the policy. Each state implemented the law according to its own timeline, which led to the phased rollout implementation that I will exploit in my empirical strategy to test for a causal impact.

While the RTE made education a fundamental right for every child in India, there were policies before that built infrastructure to make education accessible to everyone, which then enabled the Indian Government to make education a fundamental right. The Sarva Shiksha Abhiyan (SSA) is an important policy that enabled the implementation of the Right to Education Act in 2009. I give a description of this policy in the next subsection.

2.1.2 Sarva Shiksha Abhiyan

The Sarva Shiksha Abhiyan (SSA) is the Hindi phrase for "Education for all campaign". This intervention program launched in November 2000 sought to build and support primary school projects. The major components of the policy are listed below:

- Implement universal primary education by 2010, the time-frame was subsequently changed to indefinite
- Deliver good primary school education to all citizens
- Promote fair educational opportunities to minorities groups
- Improve infrastructure like drinking water, classes, and bathrooms
- Increase the quality of current teachers by providing training and funding

The policy's expenditures were divided between the states and the central governments. The central government however funds the larger share (approx. 85%), and they are in turn funded by international organizations like the World Bank and UNICEF. Past research has indicated that the SSA was successful in attracting more children to schools (Yadav, Sharma, and Birua 2018).

From the above, the SSA aimed to increase infrastructure and provide greater accessibility to all children. The RTE on the other hand made it compulsory for every child to attend school. The policies will force households from different groups to behave differently. Households that do not have high opportunity costs for their children's time through household or agricultural work would send their children to school immediately after they have access to schools, and they would have been impacted by SSA. On the other hand, we have households that might not prefer their children to go to school, but rather have them help with household work. These children would then be forced to go to school as a result of the RTE. It has been previously documented that the RTE increased school enrollment (Shah and Steinberg 2019). My thesis seeks to answer the research question "Does providing free and compulsory education for children increase their mothers' labor force participation?". Since households are impacted by the policy differently, I illustrate these dynamics using a theoretical model in the next chapter.

2.2 Relevant Literature

In order to understand the need for policies to encourage higher female labor force participation, it is imperative to understand the factors that drive these trends. India's low female labor force participation can be traced back to gender norms. Alesina, Giuliano, and Nunn (2013) find that societies that traditionally practiced plow agriculture have lesser gender equality. These communities have historically been known to have lower female labor force participation, women in leadership, etc. Applying this study to India an agrarian economy, it follows that such gender norms exist today. This could perhaps establish the connection between gender norms and low female labor force participation rates. Moreover, Bandura et al. (2001) conducted a study with 272 children and found that traditional societal beliefs directly affect children's educational aspirations and career trajectories. These children base their work-life choices mostly on these preconceived ideas rather than their actual academic achievement. Other work has found that strong gender norms directly translate to lower female labor force participation (Jayachandran 2015). The author examines data from low-income countries and finds a correlation between economic development and gender inequality. Mishra, Mishra, and Parasnis (2021) find that when crime rates against women increase, female labor force participation decreases as a result of safety concerns. Another study finds that areas with clayey soil textures tend to have lesser tasks for female labor (because of lower soil fertility and usage) and thus reduce the economic value of women in these regions relative to areas with other soil types. Thus, we can see how societal beliefs and gender discrimination in India could be driving the low female labor force participation rates (Carranza 2014).

I next explore past literature that explores the welfare effects of having low female labor force participation. (Heath 2014) conduct a study in Bangladesh to analyze the relationship between labor force participation and domestic violence. They conclude that it is imperative to increase women's household bargaining power along with increasing women's access to opportunities. Another study conducted in Brazil finds that fostering gender equality within the household is associated with long-term economic growth (Agénor and Canuto 2015). Esteve-Volart (2004) report that discrimination in the labor market against females is associated with a decrease in GDP per capita. Another study uses an intra-household distribution model and econometric techniques to find that households with higher expected female labor force participation have a lesser bias against girls in child mortality (Rosenzweig and Schultz 1982).

So far I have described the reasons for India's low female labor force participation. I then explore past literature that examines the social and economic welfare impacts that are associated with higher female labor force participation. The above discussion indicates that when women enter the workforce, it could lead to higher economic growth, better health for children, lesser discrimination towards girl children, and an overall increase in welfare. Furthermore, we have also seen how higher female labor force participation is essential for equality and socio-economic growth in these countries. Thus, it is important to study factors that could contribute to higher labor force participation in the labor force. In the next paragraph, I explore past research that has explored different factors that have led to higher female labor force participation.

Previous studies have outlined the factors that could lead to a higher representation of women in economic activities. For example, Beaman et al. (2012) study the implications of a constitutionally mandated reservation of village council and council-leader positions for women appeared to narrow the gender gap in aspirations of parents of their children suggesting a role model effect. This again highlights the importance of having female role models to positively influence women's economic representation. Fernandez, Fogli, and Olivetti (2004) find that the wives of men whose mothers worked are themselves significantly more likely to work. Other works like Bandiera et al. (2020) find using a randomized experiment that presenting employment opportunities to young women dramatically increases their likelihood of entering the labor market or being self-employed .

Rich literature has explored the particular barriers faced by women. For instance, a study suggests that in places where female labor opportunities (e.g., farming lands) are lower, the number of girl children in that particular area is also considerably lower than in non-farming lands (Carranza 2014). This happens because women do not have economic value when doing manual labor in agricultural lands, so girl children are considered unfavorable. Mathew (2015) use survey data to illustrate that falling labor force participation in India is caused by educated young women who are often discouraged by the gender pay differential in senior positions. Anderson and Eswaran (2009) show that higher labor force participation in places outside the spouse's enterprises increases women's bargaining power within households, giving them autonomy. Higher school enrollment among women has led to higher female labor force participation, fertility delays, and overall welfare improvements in women (Heath 2014).

From the above, we can see that there exists a lot of work that has extensively documented the reasons behind low female labor force participation. However, childcare could be a potential constraint that keeps women away from the household that has not been extensively analyzed in low-income countries. My research aims to fill that gap in the literature. I next analyze past literature that examines the relationship between childcare and labor force participation.

Childcare is often a major challenge for new parents. Lack of childcare could create a conflict between women's work and child-raising duties. This in turn often forces mothers to choose between motherhood and career, adding an additional time constraint (Lee and Lee 2014). For instance, Compton and Pollak (2014) find that the probability of married women entering the workforce increases by $4-10\%$ when childcare is close to them (e.g., daycare centers, mothers, or mothers-in-law living in close geographical proximity). Bick (2016) finds that providing subsidized childcare for mothers with children aged between 0 and 2 would lead to higher labor force participation.

Other studies, like Ranganathan and Pedulla (2021), find that women in a garment factory were 1.71 times higher to be present at work when the company-sponsored daycare than when they did not have access to childcare. While past literature has established that female labor force participation increases with more child-supportive policies, it is essential to note that these findings are based mostly on high-income countries where the government can support these policies. This may not necessarily be the case in developing countries, where gender norms, lack of funds, etc., would make such policies inaccessible. Children attending school may serve a similar role as childcare in that it would reduce women's household and family responsibilities, thus decreasing the opportunity cost of working. This, in turn, could encourage women to seek employment opportunities while their children are at school.

My work fills this gap in the literature where I try to establish the link between primary education and mothers' labor force participation. I use tools from classical economic theory and empirical strategies to establish this link. Specifically, my thesis tests the hypothesis *"Did the Right to Education Act increase higher female labor force participation in India?"*.

There is one paper that is particularly important to my analysis. Shah and Steinberg (2019) finds that the Right to Education Act passed in India increased the number of school-going children by 7%, test scores reduce dramatically and there is an improvement in school infrastructure. Thus, this policy had an effect on household behavior. In the next chapter, I introduce the theoretical model that will capture how the RTE influences household behavior.

Theoretical Model

3.1 Past Literature on Household Economics

The traditional neoclassical model of labor supply suggests the following maximization problem determines a person's labor force:

$$\max_{x,l} \quad U(x,l) \qquad\qquad \text{such that}$$

$$x = wh + m$$

$$t = h + l$$

According to this theory, people divide their time (t) between work (h) and leisure (l). Their consumption (x), is dependent on the wage (w) they earn and any non-wage income (m). They derive their utility from consumption (c) and leisure (l). We assume that everybody would maximize their utility. While this model provides basic intuition about labor supplies, it falls short in many dimensions. For instance, it does not account for household bargaining powers, time spent in education, the role of gender in labor force participation, etc.

These shortcomings led to a series of papers in the 1960s that proposed various models of labor supply that consider different combinations of models. Becker (1965) first proposed "The Theory of the Allocation of Time", where he accounts for time spent in household work aside from work and leisure. While Becker's theory account for time spent in the household, one of the major shortcomings of his model was the assumption that households maximize a single utility function. Today, this class of models is known as unitary household models. Singh et al. (1986) then extends this framework to include household production in an agricultural and non-agricultural context in low-income countries. It has been well established in the literature that unitary models fail to explain individual labor choices in households with more than one individual (Chiappori and Mazzocco 2017). This framework has since then served as the basis for many modern collective household models that are commonly used today.

The collective model of labor supply was first proposed by Chiappori (1992). This model overcomes the shortcoming of Becker's initial theory by assuming that households have more than one individual with their own rational preferences. The model, yet again, had a major shortcoming where it did not account for work in the household that was not leisure. To overcome this critique, Chiappori (1997) extends the model to account for household production in addition to time spent in leisure and labor force participation. This model serves as the skeleton of other modern collective labor market supplies that extends to account for household bargaining powers and unobservable preferences (Cherchye, Rock, and Vermeulen 2012; Blundell, Chiappori, and Meghir 2005). Other economists have extended the paper to include the inter-temporal version of the household labor supply model (Mazzocco 2007). These models account for the household preferences and decisions that may be time-varying. Intuitively, these models can be used to study joint versus individual taxation policies for married couples (Mazzocco 2007).

For the sake of this thesis, I start my analysis with a unitary model of household supply to get a basic intuition of how women may change their behavior in response to the RTE. My model closely follows the idea of Becker (1965) and Singh et al. (1986) as I use ideas of household production from these papers.

3.2 Model Framework

I present a simple theoretical model that represents women's labor force participation decisions. For the sake of simplicity, I assume that my household has one person (the woman). I model the household's decisions over the consumption of goods as well as the allocation of time to leisure l and total labor supplied by the household, a, which includes both labor spent in the household production activity and labor supplied to the outside labor market.

I further assume that the household does not save, meaning consumption equals expenditure, and that there is only 1 time period. The member earns wage w in the labor market, and their non-labor income (including spouse's income) is denoted by m. The member works in the labor market when all their household work demand is met and there is an additional surplus. The household is also able to hire b labor from outside the household when the household is not able to meet its labor demands internally. I next assume that the member produces goods, r, through a household production function. Some of the household-produced goods, denoted by z, are sold outside the household at price p. The rest of the household goods, denoted, y, are consumed by the households so that $r = y + z$. The house also consumes a market good x. I assume that the price of the market good x is 1.

Household production can intuitively be thought of in an agricultural and non-agricultural context. In the case of the agricultural context, the intuition is fairly simple, some of the agricultural produce is sold in the market at price p, and the rest is consumed by the household y. In the case of non-agricultural households, it can be thought of as all the household goods that are marketable (e.g. cooking, cleaning) where the household can produce the goods by themselves or purchase the same services from outside. I make the assumption that all my household production goods are marketable.

With all the model elements now defined, I present the basic framework of my household model:

$$\max_{x,y,l} U(x,y,l) \qquad \text{such that}$$

$$x = wa + m + pz - wA$$

$$y = r - z$$

$$l = T - a$$

Intuitively the member maximizes the consumption of domestic good x, household production good y and leisure l. Their consumption of goods x equals the sum of income earned from the labor market, any non-labor income, and earnings from selling domestic goods minus the wages paid to household production labor. In the constraint above, A is the total labor from the household side, and any labor hired from outside the household, b. An assumption here that follows is that the household charges itself a wage w for its' household production. Consumption of good y is dependent on the difference between the quantity produced within the household and the quantity sold outside the household. Leisure is determined after the hours spent in the labor force and household production is deducted from the total time T.

3.3 Effect of RTE

As discussed in section 2.1, the SSA increased accessibility to schools by investing heavily in infrastructure and teachers. As a result, households who did not previously send their children to school because of accessibility had the opportunity to do so after the implementation of SSA. On the other hand, the RTE forced families who were not keen to send their children to school despite its accessibility are now forced into doing so.

I extend the household labor supply model presented in the previous subsection to illustrate how households will respond to these exogenous changes from the policy. The RTE will primarily have an effect on three aspects and they can have opposing effects on mothers' labor force participation rates:

- household production - there could be a negative effect as the household loses valuable children's labor and could potentially increase the burdens on the mother for household production
- time constraint - the effect could be positive since there is no longer a need for childcare and mothers would have more time to participate in the workforce
- budget constraint - these could be positive effects like free lunches and free uniforms, or they could be negative costs like additional transportation costs

I represent the household production effect with e which stand's for the child's labor input. My total household production output is a function of adult labor A and the child's labor e. The budget constraint effect is affected by c and the time constraint is affected by d. With that, the new decision-makers problem is:

$$\max_{x,y,l} U(x,y,l) \qquad \text{such that}$$

$$x = wa + m + pz - wA + c$$

$$y = r(A,e) - z$$

$$l = T - a - d$$

where c affects the household budget constraint, e affects the households' production function and d affects the household time constraint.

Model Separability and Optimal Household Production

From the above, we can see that all the markets (like the labor and commodity markets) are complete. Singh et al. (1986) show that when markets are complete, household production decisions are separable. In other words, the household's production decisions can be made independent of the consumption and labor supply decisions. However, the households' labor supply and consumption decisions are dependent on household production. Thus, my model framework allows me to solve profit maximization independently and then substitute the solutions into the utility maximization problem.

As previously stated my household production output is r. I define r to be a function of the total adult labor input and the child's labor input. I define total adult labor supply as A where $A = a + b$. This is simply the sum of the household's adult labor supply to household production a and the hired labor b.

I assume that the functional form of the production function is $r(A, e) = (A + eq)^n$ where $0 < n < 1$ and $0 < q \leq 1$. This function also assumes that adult household labor is perfectly substitutable by hired labor. I also account for the fact that in some households' the child may not be contributing to household production work. Thus, the additive nature of this function allows for that flexibility. I include q in my function to establish that 1 hour of a children's labor is less productive than adults. The marginal productivity of the entire labor function is affected by n. With that, we have the profit function:

$$\pi = p \cdot r(A, e) - wA$$

The household revenue is $p \cdot r(A, e)$ and the cost is the market wage w times the number of hours devoted to household work A. It follows that the profit maximization problem is:

$$\max_{A} p \cdot (A + eq)^n - wA$$

The first order condition would then be:

$$\frac{\mathrm{d}\pi}{\mathrm{d}A} = pn(A + eq)^{n-1} - w = 0$$

From the above, we get that the optimal level of inputs A^* as

$$A^* = (\frac{w}{pn})^{\overline{n-1}^{\,1}} - eq \tag{3.1}$$

Substituting this into our function $r(A, e)$, we get our optimal production output point:

$$r^* = (\frac{w}{pn})^{\overline{n-1}^{\,n}} \tag{3.2}$$

We can then define the household's optimal profit function to be $\pi^* = r^* - pA^*$. In the next subsection, I will use these solutions to solve the decision-makers problem to see how the RTE would have an impact on the household's labor supply decisions.

Utility Maximization Problem

With my model elements defined and the optimal production function solved, I next present the solution to the household utility maximization problem. For the sake of simplicity, I assume that my utility function takes the form of a Cobb-Douglas Production function where $U(x, y, l) = x^{\alpha}\ y^{\beta}\ l^{\gamma}$ such that $\alpha + \beta + \gamma = 1$. I also rearrange my constraints.

$$\max_{x,y,l} U(x, y, l) \qquad\qquad \text{such that}$$

$$x + py + wl = w(T - d) + m + c + p[r^*(A, e)] - wA^*$$

Note that we have established $\pi^* = p[r^*(A,e)] - wA^*$ and we have solved for π^* because of model separability. So, the constraint can be rewritten as:

$$\max_{x,y,l} U(x,y,l) \qquad \text{such that}$$
$$x + py + wl = w(T-d) + m + c + \pi^*$$

I next solve the optimization problem by taking the Lagrange:

$$\mathcal{L}(x,y,l) = x^{\alpha}\ y^{\beta}\ l^{(1-\alpha-\beta)} + \lambda[w(T-d) + m + c + \pi^* - x - py - wl]$$

So, our first order conditions would be:

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial x} &= \alpha x^{\alpha-1}\ y^{\beta}\ l^{(1-\beta-\alpha)} - \lambda &&= 0\\
\frac{\partial \mathcal{L}}{\partial y} &= \beta x^{\alpha}\ y^{\beta-1}\ l^{(1-\beta-\alpha)}\ - p\lambda &&= 0\\
\frac{\partial \mathcal{L}}{\partial l} &= (1-\beta-\alpha)\ x^{\alpha}\ y^{\beta} l^{-(\beta+\alpha)} - w\lambda &&= 0\\
\frac{\partial \mathcal{L}}{\partial \lambda} &= [w(T-d) + m + c + \pi^* - x - py - wl] &&= 0
\end{aligned}$$

With these first-order conditions, I find the optimal conditions for the consumption of goods x, y, and leisure l and they are as follows:

$$x^* = \alpha[w(T-d) + m + c + \pi^*]$$

$$y^* = \frac{\beta}{p}[w(T-d) + m + c + \pi^*]$$

$$l^* = \frac{(1-\alpha-\beta)}{w}[w(T-d) + m + c + \pi^*]$$

Hours Worked by the Household:

I use the constraint $l = T - a - d$ and l^* to solve for a^* which in turn would give me a^* which is the optimal level of the household's total labor input.

$$a^* = -\frac{(1-\alpha-\beta)}{w}[w(T-d)+m+c+\pi^*] - d + T$$

My research question examines if the RTE would lead to an increase in off-household employment opportunities. I previously defined A^* to be the total labor input towards household production that includes both labor that is hired and the household's own labor input. So, there are 3 cases:

- If $A^* > a^*$, then the woman works only within the household and hires some labor from outside
- If $A^* = a^*$, then the woman works only within the household and there is no need to hire labor or work outside the household
- If $A^* < a^*$, then there is labor surplus, and that labor is supplied outside the household

I define formal labor force to be any employment activities that are performed outside the individual household. I represent such employment activities as h^* where:

$$h^* = \begin{cases} 0 & \text{if } A^* > a^* \\ 0 & \text{if } A^* = a^* \\ a^* - A^* & \text{if } A^* < a^* \end{cases}$$

We have previously solved for A^* and a^*. I next substitute these solutions to the h^* function to get

$$h^* = \begin{cases} 0 & \text{if } A^* > a^* \\ 0 & \text{if } A^* = a^* \\ \frac{-(1-\alpha-\beta)}{w}[w(T-d)+m+c+\pi^*] - d + T - A^* & \text{if } A^* < a^* \end{cases}$$

3.4 Comparative Statics

Comparative Statics is the study of how the optimal solutions to the model introduced in Section 3.3 would change given small exogenous changes in parameter values. My primary aim of the theoretical model is to illustrate how a change in either c, e, or d would have an effect on the consumption of good x, household production good y, and time spent in the labor force h to evaluate the effect of the household on welfare. Note that we had previously solved that:

$$\pi^* = p(\frac{w}{pn})^{\frac{n}{n-1}} - w[(\frac{w}{pn})^{\frac{1}{n-1}} - eq]$$

Outside Household Labor Supply:

I find the change in c, e and d with respect to h^*.

$$h^* = \begin{cases} 0 & \text{if } A^* > a^* \\ 0 & \text{if } A^* = a^* \\ \frac{-(1-\alpha-\beta)}{w}[w(T-d)+m+c+p(\frac{w}{pn})^{\frac{n}{n-1}} - w[(\frac{w}{pn})^{\frac{1}{n-1}} - eq] & \\ \qquad -d+T-((\frac{w}{pn})^{\frac{1}{n-1}} - eq) & \text{if } A^* < a^* \end{cases}$$

When $A^* > a^*$ or $A^* = a^*$, a change in c or e would have no impact on the outside household employment.

I first take the derivative of h^* with respect to c:

$$\frac{\partial h^*}{\partial c} = \begin{cases} 0 & \text{if } A^* > a^* \\ 0 & \text{if } A^* = a^* \\ \frac{-(1-\alpha-\beta)}{w} & \text{if } A^* < a^* \end{cases}$$

With respect to e:

$$\frac{\partial h^*}{\partial e} = \begin{cases} 0 & \text{if } A^* > a^* \\ 0 & \text{if } A^* = a^* \\ q(\alpha + \beta) & \text{if } A^* < a^* \end{cases}$$

With respect to d:

$$\frac{\partial h^*}{\partial d} = \begin{cases} 0 & \text{if } A^* > a^* \\ 0 & \text{if } A^* = a^* \\ -(\alpha + \beta) & \text{if } A^* < a^* \end{cases}$$

When $A^* < a^*$ they translate to the following:

- an increase in c will lead to a decrease in h^* and a decrease in c will lead to an increase in h^*
- an increase in e will lead to an increase in h^* and a decrease in e will lead to a decrease in h^*
- an increase in d will lead to a decrease in h^* and a decrease in d will lead to an increase in h^*

An increase in c will discourage women to enter the labor force since the budget constraint relaxes, however a decrease in c will encourage her to enter the labor force because of the additional need for income.

An increase in e will increase the household's production activities which in turn may lead to more goods being sold. This, in turn, may lead to increased adult labor supply as the household's production responsibilities are substituted by children's labor input. However, a decrease in e will reduce the input towards household production output and this in turn would force the mother to perform household activities and reduce outside employment opportunities.

An increase in d will increase childcare constraints and this in turn would reduce off-household labor supply. A decrease in d will decrease childcare constraints and this in turn would incentivize the mother to enter the labor force.

Consumption of Market Goods:

The optimal function of x^* is:

$$x^* = \alpha[w(T-d) + m + c + p(\frac{w}{pn})^{\frac{n}{n-1}} - w[(\frac{w}{pn})^{\frac{1}{n-1}} - eq]$$

We take the partial derivative of x^* with respect to c:

$$\frac{\partial x^*}{\partial c} = \alpha$$

With respect to e:

$$\frac{\partial x^*}{\partial e} = \alpha wq$$

And with respect to d:

$$\frac{\partial x^*}{\partial d} = -\alpha w$$

These partial derivatives imply that:

- an increase in c will lead to a increase in x^* and a decrease in c will lead to an decrease in x^*
- an increase in e will lead to an increase in x^* and a decrease in e will lead to a decrease in x^*
- an increase in d will lead to a decrease in x^* and a decrease in d will lead to a increase in x^*

An increase in c has a positive effect on the household's consumption of market good x and a negative c will decrease the household's consumption of market good x.

A decrease in e will lead to lesser household production which could reduce the quantity sold outside the household which would reduce the ability to consume x. An increase in e will lead to higher household production and increase the ability to increase more x.

An increase in d will increase childcare responsibilities which in turn will reduce the ability to allocate time to work and as a consequence will reduce their inability to consume market good x. When there is a decrease in d, it will increase the ability to consume more goods x.

Consumption of Household Production Goods:

The optimal function function y^* in Section 3.3 is:

$$y^* = \frac{\beta}{p}[w(T-d) + m + c + p(\frac{w}{pn})^{\overline{n-1}}^{n} - w[(\frac{w}{pn})^{\overline{n-1}}^{1} - eq]$$

I first take the derivative with respect to c:

$$\frac{\partial y^*}{\partial c} = \frac{\beta}{p}$$

I next the derivative with respect to e:

$$\frac{\partial y^*}{\partial e} = \frac{\beta w q}{p}$$

And finally with respect to d:

$$\frac{\partial y^*}{\partial d} = \frac{-\beta w}{p}$$

The interpretations are:

- an increase in c will lead to an increase in y^* and a decrease in c will lead to a decrease in y^*
- an increase in e will lead to an increase in y^* and a decrease in e will lead to a decrease in y^*
- an increase in d will lead to a decrease in y^* and a decrease in d will lead to an increase in y^*

An increase in children's labor input e will increase the household's production, so it allows for more consumption of y^*. A decrease will have the opposite effect and reduce the consumption of y^*.

An increase in c will increase the consumption of household goods as it will allow for more household production goods to be consumed by the household rather than sold outside for additional income. A negative c will however have the opposite effect on the budget constraint and this in turn would reduce the consumption of y^*.

An increase in d increases childcare constraints and this would reduce the household's time allocation to labor activities and thus reduce the consumption of y^*. On the other hand, a decrease in d will increase the household's ability to produce more goods and thus will increase y^*.

3.5 Discussion

Summary:

From the above, we can see that mother's labor supply increases when childcare constraint d decreases, children's labor input e increases and the budget constraint effect c is negative. An opposite effect on these variables would decrease female labor force participation. It is important to note that while some of the effects are positive for the overall household welfare like decreasing childcare constraints, other effects like increasing children's labor input may in turn reduce overall household welfare. Thus, it is important to check for overall welfare implications when implementing policies.

This policy affects other aspects of the household as illustrated in Section 3.4. A positive c would increase consumption of marketable goods x and household production good y since it relaxes the budget constraint. A negative c however would have the opposite effect. A positive e would increase the households' consumption of x and y as it would allow the mother more time for other activities like household production and entering the labor force because of additional input from the children's labor. A negative e would however have the opposite effect. A positive

d, increases childcare constraints and reduce the consumption of goods x and y, since the mother may not have time for off-farm employment anymore. A negative d relaxes childcare constraints and would have the opposite effect and increase the consumption of goods x and y.

Limitations:

It is important to note that my model suffers from some serious limitations. For instance, my model assumes that there is only one person in the household, past literature has shown that this could at times lead to misleading predictions (Chiappori and Mazzocco 2017).

Moreover, my model assumes that the household's markets are complete and can therefore apply the concept of separability. This may be different in the real world as some markets like the labor market could be incomplete in low-income communities. This could potentially lead to biased production output.

Another limitation of my model is the way my formal labor supply function is set up. My current model assumes that a household would always meet its internal labor demands first and only the surplus would work in the formal labor surplus. In reality, this may not be true and the household can choose to work in outside employment opportunities even when their internal labor demands are not met.

Other limitations include the fact that my model assumes that households do not save and that there is only one time period. Moreover, my model does not solve corner solutions. In other words, it does not tell us if a woman would enter/exit the labor force but rather if her overall hours increased or decreased. This is a major limitation since my research question aims to identify if women would enter/exit the labor force. My model currently gives us if the time she spends in the labor force increases or decreases (interior solutions), but not the corner solutions.

My research question primarily looks at the effect of RTE on female labor force participation. My theoretical model predicts that the effect of RTE is dependent on how the household is affected by the RTE (through variables c, d e) and if there is a need for off-farm employment opportunities for the household. In the next chapter, I test my hypothesis using data and an empirical strategy.

Empirical Model

4.1 Data

I use data from the Employment and Unemployment Surveys, which is accessible from the Indian National Data Archive. This archive is managed by the Indian Ministry of Statistics and Programme Implementation. The primary purpose of the Employment and Unemployment Surveys, part of the National Sample Surveys (NSS), was to collect more information on various aspects of the labor force at both the national and the state levels.

These surveys provide information such as the region, age, education, gender, the standard of living, industry and occupational categories, informal sector versus formal sector labor, etc., The surveys are divided into 4 further sub-rounds where each sub-round lasts for 3 months. Random households are sampled in each sub-round across all states. This makes my data set a repeated cross-section survey. The unemployment/employment status in these households is determined by the primary activity status asked using three different reference periods: one year, one month, and one week.

The sampling strategy uses a stratified multi-stage design. The stratified sampling technique is when researchers divide the population into homogenous sub-populations and a multi-stage design is when these sub-populations are divided into clusters for drawing samples. The survey was collected using questionnaires at the household level.

The more extensive National Sample Survey (NSS) happens every five years, but employment and unemployment surveys occur every two years, and around $50,000$ households are surveyed nationwide. Since the act was first treated in April 2010 and was implemented in 3 phases until 2012, I use the surveys for the following periods:

- July 2009 - June 2010,
- July 2011 - June 2012.

The phased rollout nature of the policy creates a quasi-experimental research design that enables the implementation of an event study model. The graph below illustrates the timing of the survey years versus the actual dates a particular state was treated. It also shows the different sub-rounds in each survey, so, we have data to check for the parallel-trends assumption and have sufficient periods that would serve as counterfactual.

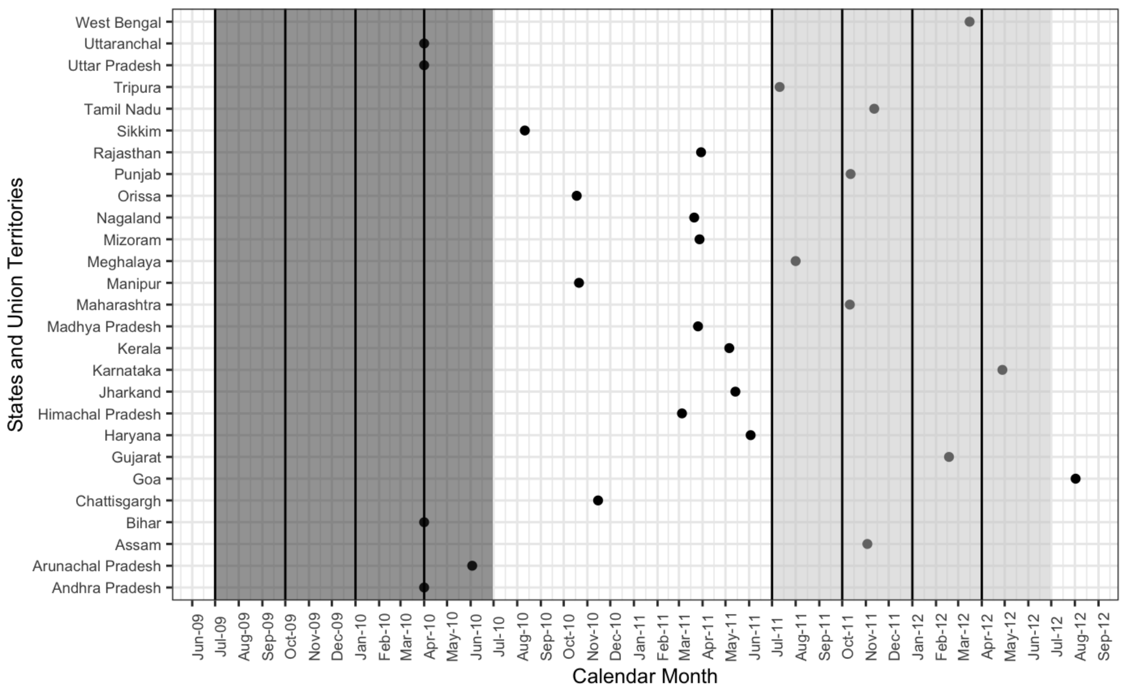

Figure 4.1: Survey Data versus Policy Implementation

Figure 4.1 depicts the graph of my survey data versus the policy implementation date. Each survey round is divided into four sub-rounds. Since we have household survey data throughout the year, it would give us the post-treatment data, even for the states that were treated at the start of 2012. So, there is one survey round to check for pre-trend data and two more survey rounds during the phased rollout implementation.

There were some months outside my survey periods that had very few datapoints. This could be because some survey rounds ended in August 2010 instead of July 2010. I drop the observations from such time periods as they have very few data points.

4.2 Descriptive Statistics

My thesis aims to answer the research question "Does providing free and compulsory elementary education increase mothers labor force participation in India?" Our variable of interest is the proportion of mothers in the labor force. My data sample includes women between the age of 20 and 50, who have at least one child in the household. I limit my sample to represent the mothers who most likely have children aged between 6 and 14.

Table 4.1 gives a detailed description of the number of women in my sample who belong to different demographics. The numbers below represent the sample data from 2009 - 2012:

Table 4.1: Demographic Groups

Category	Number	Percentage
Geographic Area		
Urban	26,518	34.09%
Rural	51,270	65.90%
Education		
Literate	50,964	65.34%
Not Literate	26,824	34.60%
College Graduate	6,498	9.06%
Not a College Graduate	65,216	90.93%
High School Graduate	12,570	83.25%
Not a High School Graduate	65,216	16.72%
Social Group*		
Disadvantaged Groups	23,870	30.68%
Not Disadvantaged Groups	53,917	69.31%
Marital Status		
Currently Married	72,304	92.95%
Currently Not Married	5,478	7.04%
No. of People	77,788	
No. of Households	59,882	

* I define Social Groups based on the caste system in India. Disadvantaged groups are those who belong to the Scheduled Caste/Scheduled Tribe Caste

Table 4.1 we can see that women tend to live in rural areas, without a high school or college education, and are mostly married in my data sample. I next define if a woman is in the labor force or not. The survey asks each member of the household about their "Usual Principal Activity Status" in the last week. I label anybody who performs domestic duties only, as unpaid family workers, looking for employment as not in the labor force.

Table 4.2 provides information on the percentage of women in the labor force in each of the demographic categories:

Table 4.2: Labor Force Participation by Demographic Groups

Category	In Labor Force	Not in Labor Force
Geographic Area		
Urban	13.65%	86.34%
Rural	15.14%	84.58%
Education		
Literate	12.58%	85.83%
Not Literate	19.05%	80.94%
College Graduate	21.86%	78.13%
Not a College Graduate	14.16%	85.83%
High School Graduate	14.61%	85.38%
Not a High School Graduate	15.84%	84.15%
Social Group		
Disadvantaged Groups	21.08%	78.91%
Not Disadvantaged Groups	12.03%	87.96%
Marital Status		
Currently Married	14.09%	86.90%
Currently Not Married	37.42%	62.57%
No. of People	77,788	
No. of Households	59,882	

From Table 4.2, we can see that women who live in disadvantaged groups, are not literate, and are not currently married tend to participate in the labor force more than their counterparts. Households that belong to disadvantaged social groups or where the members are not educated are probably correlated to low-income households. These households may have a greater need for income, which in turn reflects in the higher female labor force participation rates. Similarly, single mothers will likely have to enter the labor force themselves to support their families which again reflects in the table above.

In this section, I present summary statistics from my data sample which consists of mothers between the age of 20 and 50 to see how different factors could influence mothers' labor force participation. As a first step, I compare mothers' labor force participation before and after the policy was implemented. Since the policy has a phased rollout nature I treat the time of treatment for each state as time 0. The figure below shows the trends of mothers' labor force participation relative to the months prior to and after the treatment occurred, hereafter referred to as relative months.

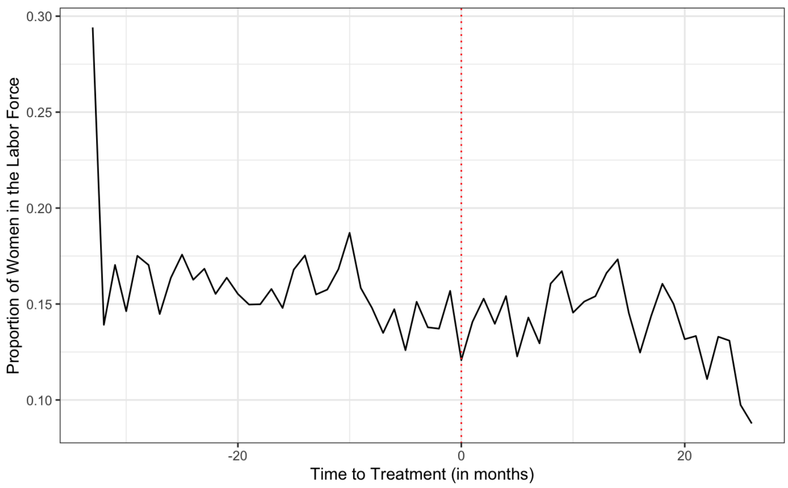

Figure 4.2: Mothers' Labor Force Participation in Relative Months

The trends in female labor force participation seems to be slowly declining as time progresses as seen in Figure 4.2. This is consistent with past research that has found a decline in female labor force participation. So, the policy does not seem to increase female labor force participation overall. This can be explained by the fact that some households may benefit more from this policy than others and hence may not reflect when examining all women. Some of the factors that could potentially influence female labor force participation in India besides childcare are education levels, marital status, the safety of women, social group (for example schedule caste), and access to employment opportunities (rural/urban) as shown in

Table 4.1. Thus, I check for trends within these subgroups next and examine this using multiple subsets of data.

Education Level

I first look at how this policy would affect women based on literacy status. I define literate as anyone who can read and write simple sentences in at least 1 language (as defined by the Indian Government). I check for trends in the labor force participation in the relative months of treatment below:

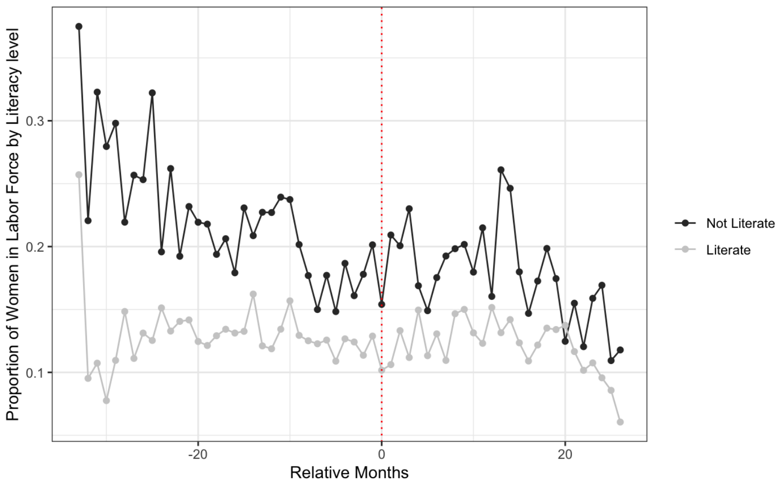

Figure 4.3: Female Labor Force Participation among Literacy Groups

In Figure 4.3 we can see that women who are not literate tend to participate in the labor force at higher rates than women who can read and write. This trend could potentially be explained by the fact that women who are not literate are also the ones who live in low-income households.

Literary rates, however, are not an indicator of education levels since they are loosely defined as anybody who can read and write. I next look at women who have completed college versus those who did not.

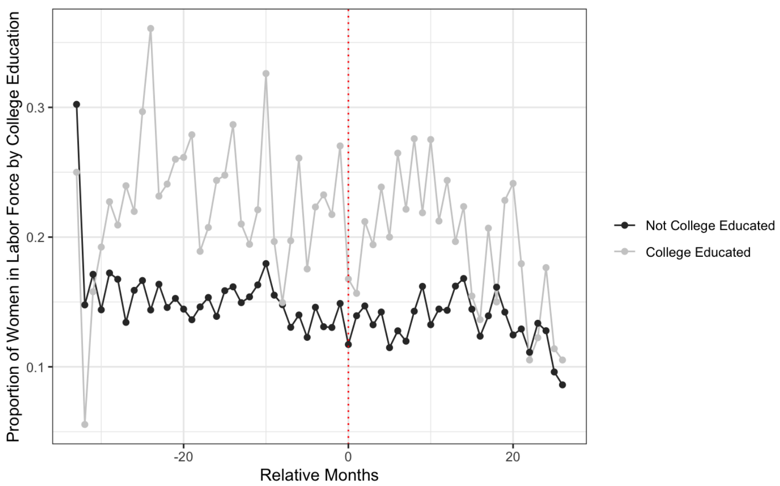

Figure 4.4: Female Labor Force Participation among College Graduates

Figure 4.4 shows that college-educated women tend to enter the labor force at higher rates leading up to the time the policy was implemented. As seen in the sample statistics table, the number of college-educated women is very low. This trend is potentially driven by women who are easily able to find work when the time constraint is relaxed because of free child care given their additional education qualifications

Marital Status

Marital status of Women could be another factor influencing mothers' labor force participation. Single mothers could face additional constraints in the household (like time and income) compared to married mothers. This could incentivize them to enter the labor force at higher rates as reflected in the graph below.

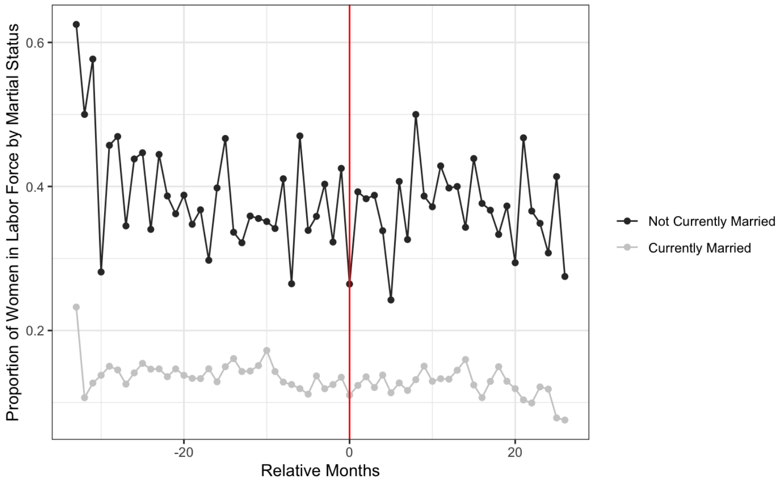

Figure 4.5: Female Labor Force Participation based on Marital Status

This shows that female labor force participation is influenced by women's marital status as on average single women tend to enter the labor force more than married women, regardless of the policy change.

Social Group

India has a long history of its caste system. Women who belonged to disadvantaged caste groups tended to have less access to education or other opportunities, restricting the scope for upward social mobility. Moreover, these groups are, more often than not, governed by stricter gender norms and thus perform certain kinds of jobs for income (for example household work). This is reflected in the graph below.

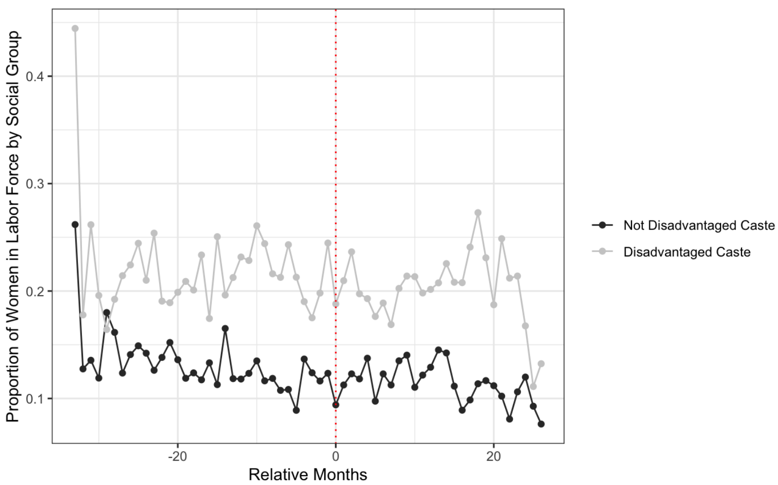

Figure 4.6: Female Labor Force Participation among Social Groups

Women in disadvantaged castes would tend to work in unskilled jobs and so these jobs are accessible to women thus, women from these social groups tend to work in these groups at higher rates.

Geographic Area

Another factor that could influence female labor force participation is the geographical area. For instance, women who live in rural areas may find it harder to find higher-paying job opportunities and this may discourage them from entering the labor force or they may all be performing other work like household work for example.

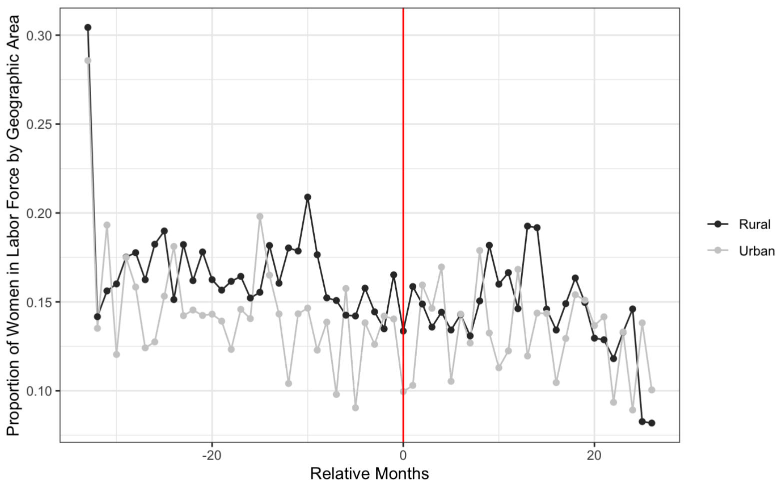

Figure 4.7: Female Labor Force Participation among College Graduates

From Figure 4.7 we can see that on average, labor force participation between the two groups does not differ much. So, geographic regions may not be a significant factor influencing female labor force participation.

State

There are 28 States in India each with its own culture, language, traditions, etc. This translates to different gender norms and preferences for women's choice to enter the workforce. Thus, it is important to check for trends in different states when trying to measure the causal effect. The following graph examines this trend:

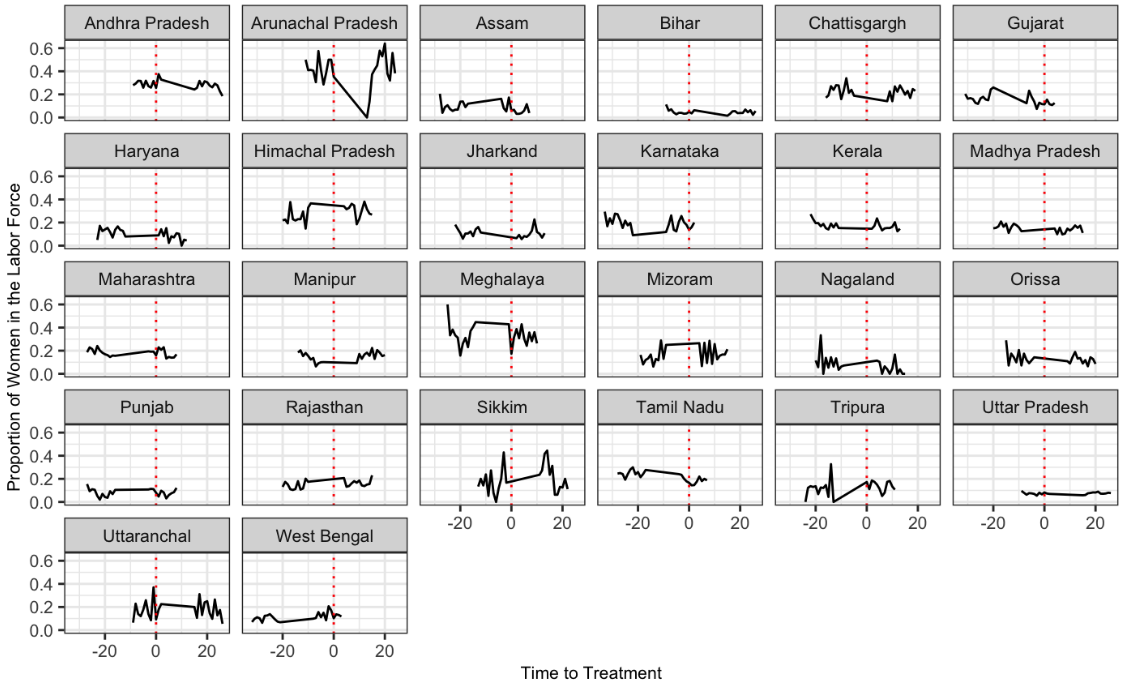

Figure 4.8: Female Labor Force Participation among States

As evident from the graph above, we can see that each state is different in the labor force trends and participation rates. The sharp fluctuations in data can be attributed to the fact that the number of sample data points for those particular states at a particular relative month is low. Therefore, it is imperative to account for this in the identification strategy in the next section.

4.3 Identification Strategy

To answer my research question, "Did the Right to Education Act encourage higher female labor force participation ?". I need to compare the effects of the policy to a counterfactual (a scenario where the policy is not yet implemented) to measure the impact of the policy. However, my policy was implemented in all states in India, making it difficult to have a counterfactual. The phased implementation of the policy, however, gives us the "not yet treated" states as potential counterfactual units. I intend to explore this variation in policy timing to draw a causal inference. I explore different empirical strategies in this section. I first use a simple difference-in-differences technique with one treatment and control group. I then extend that model to a two-way fixed effect regression model with staggered timing. In order to overcome the limitation of that model, I then implement a method proposed by Santanna and Callaway (2021).

4.3.1 Difference-in-Differences

A differences-in-differences method is a quasi-experimental approach that compares the outcome variable of the treatment group (the policy is implemented) to the control group (the units where the policy is not yet implemented). Important assumptions of this approach are the parallel trends assumption and the stable unit treatment value assumption where there are no other time-varying factors that could be influencing trends between the control and treatment groups and no control group contamination.

The canonical differences-in-differences model is as follows:

$$y_{st} = \beta RTE_s + \gamma post_t + \delta(RTE_s \cdot post_t) + \alpha + \epsilon_{st}$$

where y_{st} is a dummy variable that indicates if a woman is in the labor force in a particular state s in month t. The independent variables attempt to capture the effect of the RTE on female labor force participation. RTE_{st} is a dummy variable that indicates if state s has implemented the policy within our estimation time frame. $post_t$ is a dummy variable that indicates if the time period is after the policy is implemented in that state. The interaction term $(RTE_s \cdot post_t)$ estimates the impact of the policy on women's labor force participation. α is the vector of the control variables I include in my model. In particular, they are college education, and marital status as labor force participation differs within these groups as previously discussed.

Model Assumptions:

A differences-in-differences model requires all states to be treated at the same time and a few other states to not be treated at once which is different from the phased implementation design of my data. This makes it difficult to implement a standard framework to measure the causal impact in all the states.

Therefore, to address this issue, I restrict my dataset as follows. I take the states that were treated in April 2010 and denote these as the treated group. I use the states that were treated after January 2012 as my control group. I limit data to surveys from July 2009 to December 2011. Table 4.3 further illustrates my treatment and control groups along with their date of treatment:

Table 4.3: Differences-in-Differences: Treatment and Control Groups

Treatment Group	Treatment Date	Control Group	Treatment Date
Andhra Pradesh	04/01/2010	Gujarat	02/08/2012
Bihar	04/01/2010	West Bengal	03/16/2012
Uttar Pradesh	04/01/2010	Karnataka	04/28/2012
Uttaranchal	04/01/2010	Goa	08/02/2012

(1)Parallel Trends Assumption:

An important assumption of this framework is the parallel trends assumption. It requires the treatment and control groups to follow parallel trends in the absence of treatment. Since I do not have data to assess this validity, I compare the treatment group to the control group (treatment was not yet implemented). I present the parallel trends from the pre-treatment periods in Figure 4.9:

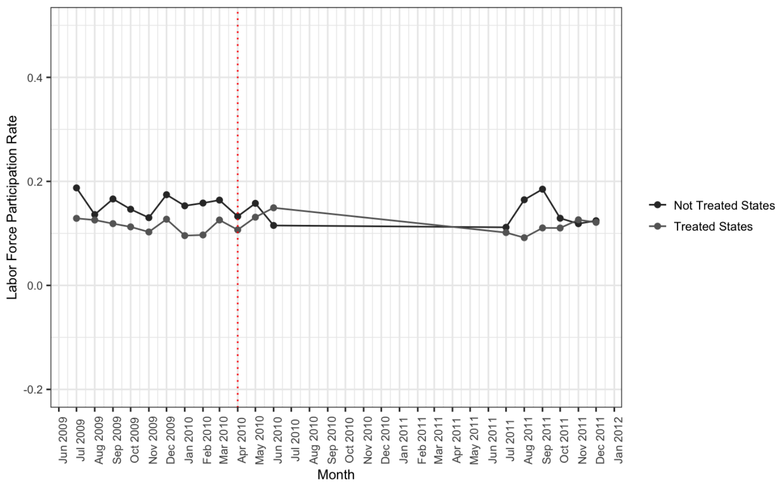

Figure 4.9: Female Labor Force Participation Rates before and after treatment

The time of treatment is highlighted by the red vertical lines. We can see that in general, the treatment and control groups seem to follow similar labor force participation rates. Thus, our assumptions hold for the differences-in-differences specification.

(2) Stable Unit Treatment Value Assumption (SUTVA):

This assumption requires that the treatment assigned to one group does not affect the potential outcome of other groups. This assumption is likely to hold in the case of my study as each state is required to draft its own RTE rules. Moreover, increase female labor force participation is not a direct effect of the RTE but rather a consequence of the effect within the household. Thus, since the fact that one state is treated does not alter the behavior of mothers in other groups.

Results:

In this subsection, I first calculate the average mean to check for differences pre and post-treatment in my treatment and control groups. The table shows the proportion of women in the labor force in each of these categories. Table 4.4 illustrated my results:

	Pre-Treatment	Post-Treatment	Difference
Treated Group	0.1385194	0.1156150	0.0229044
Control Group	0.1557281	0.1146146	0.0411135
Difference	-0.0172087	0.0010004	

Table 4.4: Average Mean Pre and Post-Treatment

From the above table, we can see that mothers' labor force participation dropped for both the treatment and control groups over time which is in accordance with past literature. However, it is important to note that the drop was smaller among the treated group than the control group, suggesting the policy could have encouraged some women to enter the labor force in the treated states. I next check for an effect using an Ordinary Least squares Regression.

I present the regression results from the difference-in-differences model specified previously. I use a linear probability model for my estimates to check if the policy had an impact on female labor force participation in the treated states. My data sample after restricting my sample to the states mentioned in Table 4.3 and from June 2009 to December 2011 has $24,422$ women and represents $18,798$ households in the 8 states used for this model. Table 4.5 presents classic differences-in-differences model and a second model with additional control variables:

Table 4.5: Estimates from the Differences-in-Differences Model

	Dependent variable:	
	Female Labor Force Participation	
	(1)	(2)
States Treated	-0.041^{***}	-0.037^{***}
	(0.006)	(0.006)
Post Period	-0.017^{**}	-0.017^{**}
	(0.007)	(0.007)
States Treated*Post Period	0.018^{**}	0.017^{*}
	(0.009)	(0.009)
College Educated		0.050^{***}
		(0.008)
Marital Status		-0.233^{***}
		(0.008)
Constant	0.156^{***}	0.367^{***}
	(0.005)	(0.009)
Observations	24,422	24,421
R^2	0.002	0.035
Adjusted R^2	0.002	0.035
Residual Std. Error	0.331 (df = 24418)	0.326 (df = 24415)
F Statistic	19.139^{***} (df = 3; 24418)	176.869^{***} (df = 5; 24415)
Note:		*p<0.1; **p<0.05; ***p<0.01

The interaction term RTE_s*Post_t is our coefficient of interest and is statistically significant at the 0.05% level. The coefficient suggests that the RTE increased female labor force participation by 1.8%. This implies that it is possible to conclude that the Right to Education Act had an impact on female labor force participation decisions in India. The negative coefficients on RTE_s indicate female labor force participation rates in the pre-treatment period in the treatment group were lower than in the control group. Post_t tells us that female labor force participation decreased after the policy was implemented within the control group.

The model with additional control variables also yields similar results where our coefficient of interest is positive and statistically significant but only at 0.1% level. However, it is worth noting that the t-stats for both the models is similar. The results from the theoretical model suggest ambiguous results, however, my first empirical strategy suggests that female labor force participation increased after the RTE in certain states.

Limitations of the Differences-in-Differences Model:

Though a good first step, this model has limitations that could potentially lead to biased estimates. For instance, I did not consider all the states in India but rather chose 8 states for my treatment and the control group is fully random. For instance, the states that passed the law first would have different political influences than the states that passed the law last. So, it may not be telling us the whole story. Another limitation is that the results of my policy could have changed long-term and I do not account for that in my model. As a next step, I implement a more advanced event-study framework also known as Two-Way Fixed Effects Regression with Staggered Timing that helps me overcome some of the limitations mentioned above.

4.3.2 Two-Way Fixed Effects with Staggered Treatment

A two-way fixed effects regression is a generalized version of the canonical difference-in-differences described in Section 4.3.1. It allows researchers to have multiple groups and treatment periods. The model relies on time and state-fixed effects to control for the time in varying factors between multiple groups and periods. In the context of my thesis the Right to Education Act is a staggered adoption as my states are treated at different times across 3 years and one state is not treated within my data sample. I drop this state (Goa) from my data sample to avoid using that as the sole counterfactual. The generalized version allows me to test my hypothesis across all states in India. Thus, this model allows me to overcome one of the major limitations of the differences-in-differences model. I next present the mathematical exposition of a two-way fixed effects regression:

$$
\begin{aligned}
y_{st} = \alpha_t + \beta_s + \gamma \text{Time to Treatment}_t + \delta \text{Treated States}_s \\
+ \lambda(\text{Time to Treatment}_t \cdot \text{Treated States}_s) + \epsilon_{st} \quad (4.1)
\end{aligned}
$$

where γ indicates if the household is treated at time t, δ represents if the state s received treatment and λ captures the impact of the RTE on female labor force participation in relative period t at state s. I then have α_t which represents the time-fixed effect and β_s which captures state-fixed effects. This model measures the impact of the RTE across different treatment timings by adding states and time effects to control for time-invariant factors between these groups. Equation 4.1 is estimated using OLS and can be unbiased only if 3 assumptions hold which I discuss below.

Model Assumptions:

I next discuss the model assumptions required for Equation 4.1 to give unbiased results.

1)Parallel trends in baseline outcomes

Similar to the classic differences-in-differences discussed in Section 4.3.1, the two-way fixed effects regression also requires that treatment and control groups should share similar baseline outcomes. The units that violate this assumption should be dropped from the estimation. In the case of my model, the state of Jammu and Kashmir is never-treated but the political and economic disturbances could potentially lead to different baseline outcomes between the treatment and control groups. I also drop the state of Goa from my data sample as it was not treated within my data time frame and could lead to biased estimates if it serves as the only counterfactual. Thus, I drop tgese state from my data sample.

I check my parallel trends assumption using the pre-trend data in my model. For this assumption to hold, none of my estimates before treatment (time 0), should be different from zero. In other words, I expect that none of my coefficients before treatment will be statistically significant when I run the event study version of equation 4.1. When they are not statistically significant it implies that there are no obvious trends in the data between the treatment and control groups in the data sample. I present my coefficient plot in Figure 4.10 and for the sake of this assumption we will concentrate only on time periods before $t = 0$:

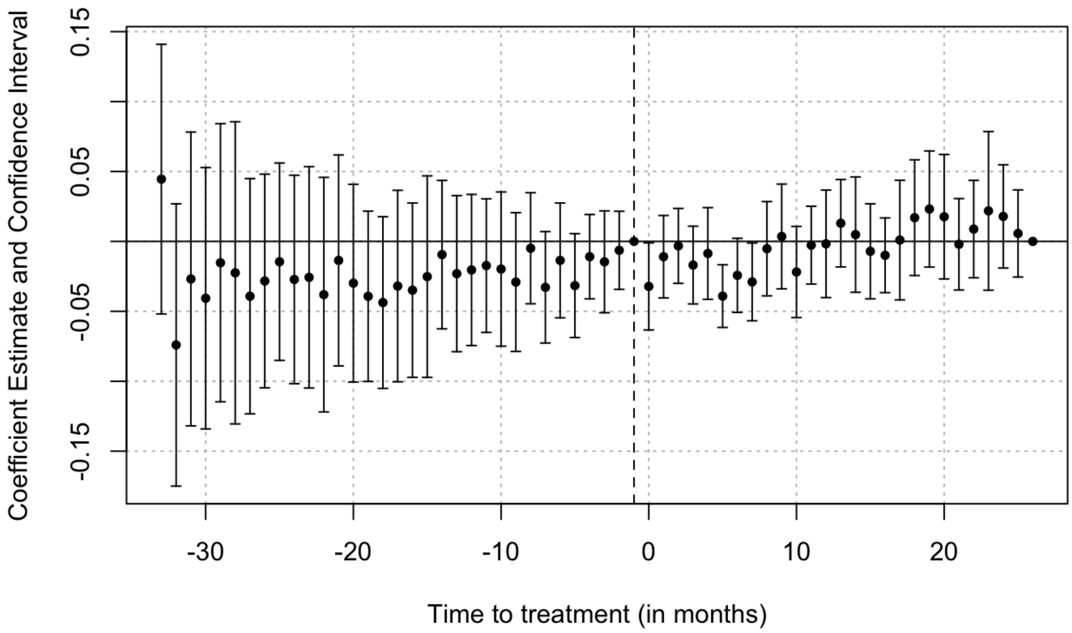

Figure 4.10: Coefficient Estimates from an Event-Study Fixed Effects

From the above, none of the coefficients are statistically significant. Thus, the pre-tends assumption is now satisfied. I also present the corresponding coefficient estimates in Appendix A.1 to show the exact estimates and statistical significance at the 5% level.

2) No anticipatory behavior prior to treatment:

The next assumption is that the treated units should not know about the treatment when they could potentially alter their behavior in the relative periods before the treatment. In the context of my study, it is important to note the differences between the Right to Education Act and the Sarva Shiksha Abhiyan (SSA).

As discussed in Chapter 2, the SSA improved accessibility to primary school, and the RTE mandated that every child must attend elementary school. My study specifically looks only at the RTE. Even though there was some kind of anticipation or trends prior to the RTE, the RTE by itself increased school enrollment (Shah and Steinberg 2019). Thus, my empirical analysis focuses on these households and the causal impact of mandating primary education on female labor force participation. So, the second assumption also holds.

3) Treatment effect homogeneity:

This assumption requires that the treatment effects remain the same across every time period. Intuitively, this would require the policy to have the same effect on female labor force participation both 1 month after the policy and 12 months after the policy. This assumption may not hold in the context of the RTE. For instance, women may not immediately enter the labor force as soon as the children leave for school (1 month after the policy), but would rather take some time adjusting, prepping for school, etc., and would then consider entering the labor force. The effect in the later months would be different from month 1, and thus, this assumption could potentially not hold in the context of my study. Despite its limitations, I use this model to gain a preliminary intuition of the results.

Results:

I next run the Two-Way Fixed Effect Regression Model with staggered timing for all States (except Jammu and Kashmir and Goa) from June 2009 to July 2012. My treatment is staggered with the first treatment occurring in 04/01/2010 in 4 States. My final results include $77,788$ individuals and $59,882$ across the 2 survey rounds mentioned. I run the regression specified in Equation 4.1.

Similar to the differences-in-differences without staggered treatment (Section 4.3.1), I run two sets of model. My first model uses Treated States as the independent variable which represents all the individuals that were surveyed in a state s that was treated at time t of the survey. I then run the same model with additional control variables for college-educated and marital status. Figure 4.11 illustrated my coefficients for the model without any control variables:

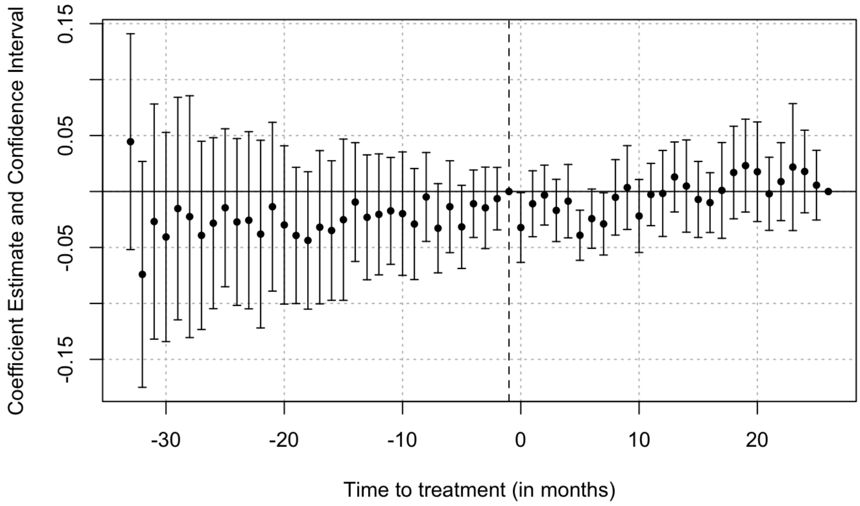

Figure 4.11: Coefficient Estimates without Control Variables

Figure 4.12 shows the coefficients for the model with control variables. The coefficient estimates are not very different from Figure 4.11.

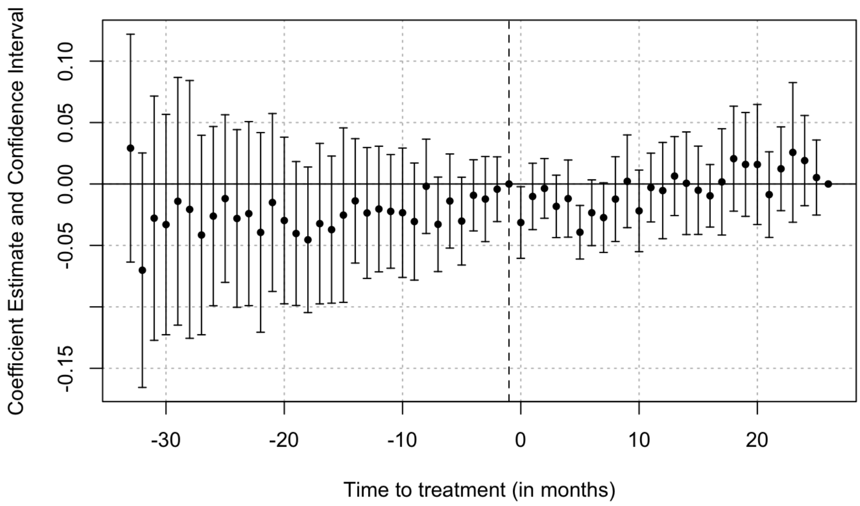

Figure 4.12: Coefficient Estimates with Control Variables

From Figure 4.11 and Figure 4.12, we can see that most of the coefficients of interest are not statistically significant. However, relative months $5-7$ are negative and statistically significant at the 0.05% level. This indicates that female labor force participation could perhaps have had a transient pattern. For instance, as soon as the policy was introduced it could have caused short-term shocks and the effect could have then worn off. However, in the longer term, the statistically insignificant results indicate that I do not have sufficient evidence to conclude that the RTE had an impact on mothers' labor force participation. On one hand, it could have reduced labor force participation by adding to the time constraint or by relaxing the household budget constraint. On the other hand, it could have had the opposite effect by relaxing the time constraint (free childcare).

However, these results should again be treated cautiously. There are a number of serious limitations this model suffers which have been documented extensively in recent literature (Goodman-Bacon 2021). My next subsection discusses this aspect of the model in detail.

Limitations of the Two-Way Fixed Effects Model:

Economists have traditionally used a two-way fixed effects regression model when the treatment timing is staggered. However, recent literature has highlighted the potential biases that could arise from this estimator. I briefly describe this in Assumption (3). One of the strong assumptions required for Equation 4.1 to be an unbiased estimator is that treatment effects should be homogeneous. When this assumption fails to hold as is likely the case with my model it can lead to misleading coefficients (Goodman-Bacon 2021). When there is a heterogeneous treatment effect, the decomposition includes information not only about that particular time period t but also from other time periods preceding and succeeding it (Sun and Abraham 2021).

In response to these limitations, there have been different papers that propose alternative estimators when assumption 3 is violated (Sun and Abraham 2021; Callaway and SantAnna 2021; Borusyak, Jaravel, and Spiess 2021). They each have their unique solution to the problem and suit different experimental designs. Roth et al. (2022) provides a synthesis of the pros and cons of the various different estimators. I use the Callaway and SantAnna (2021) estimator since it allows me to use "not-yet-treated" units as controls. This is an advantage since estimators like Sun and Abraham (2021) use "last to be treated" as control units. This is important for my research design since Sun and Abraham (2021) would only use the States of Goa and Karnataka as counterfactuals for all states. On the other hand, Callaway and SantAnna (2021) use information from all not-yet-treated states at time t, to draw an estimate which is a more realistic counterfactual. Thus, I next use the Callaway and SantAnna (2021) estimator to overcome some of the limitations that a general two-way fixed effects model with staggered timing poses and would enable me to better answer my research question.

4.3.3 The Santanna and Callaway Estimator

In this subsection, I discuss in greater detail the estimator proposed by Callaway and SantAnna (2021). I first introduce notation that is commonly used by economists when discussing these models.

An event study requires a random sample of N units observed over $T+1$ time periods. I define the outcome variable as $Y_{i,t}$ for each i in N and t in set T. I next define the treatment variable $D_{i,t}$ as a dummy variable that is 1 to indicate treatment for unit i at time t and 0 otherwise. Based on the time of the first treatment t, we categorize the units into disjoint cohorts (g) where $g \in \{0, 1, ..T, \}$. So, g is determined based on when the state first received treatment. The treatment effect is then the difference between the counterfactual and the treatment variable $Y_{i,t}$. Thus, our coefficient of interest here would be the average of unit-level treatments at a given relative period across units first treated at time e. A relative period can be defined as the difference between the date of the survey and the date of treatment. The mathematical exposition of an event-study model can be written as follows:

$$Y_{s,t} = \alpha_s + \gamma_t + \sum_{l=-K}^{-2} \mu_l D^l_{s,t} + \sum_{l=0}^{L} \mu_l D^l_{s,t} + \epsilon_{s,t}$$

Here, $D^l_{s,t}$ is an indicator variable for state s, being l periods away from initial treatment at time t. α_s stands for state-fixed effects and γ_t stands for month-fixed effects. Thus, μ_l is the coefficient of interest here that captures the treatment effects for a given relative period l.

Estimation Procedure:

The paper proposes calculating the parameter of interest using 3 steps:

- Calculating the policy-relevant disaggregated causal parameters for each group g at time t
- Summarize the disaggregated parameters to get the event study estimates

- Estimation and inference

I next discuss how I calculate these causal parameters for my thesis. To estimate the coefficient of interest, the authors use the concept of the group-time average total effect on the treated (ATT). Intuitively, the ATT can be thought of as the difference between the expected value of the treatment group and the expected value of the counterfactual at a particular time period t. The comparison group in my context would be "not-yet-treated". If I am looking at measuring the ATT of State A and State A is treated at time t, but State B and C are only treated at time $t+1$ units then conditional on the parallel trends assumption I use State B and C as my counterfactual for State A to measure the coefficient of interest for time t. This also implies that my estimates are only possible for months where at least 1 state is not treated.
The ATT is calculated by the following formula:

$$ATT(g,t) = E[Y_t(g) - Y_t(0)|G_g = 1] \text{ for } t \geq g$$

The $ATT(g,t)$ is the difference between the average of mothers' labor force participation in the treated group g and the average of the not-yet-treated units at time t. This model fixes group g and calculates the average treated effects for an evolving time t, allowing us to see how average treatment effects vary across different times. I calculate this for every group g. I also focus only on post-treatment variable $t \geq g$, since as per the no-anticipation effect assumption all pre-treatment variables are 0.

My model uses the "Event Study/dynamic treatment effects" method of aggregation. This method accounts for the fact that the effect of a policy intervention may depend on the length of exposure it has, which best suits my experiment design. In the next subsection, I discuss different model assumptions that need to hold to make this estimator precise.

Model Assumptions

The model assumptions for the Santanna and Callaway Estimator are very similar to the standard two-way fixed effects regression with staggered timing assumptions. I use the same data set as used in subsection 4.3.1.

(1) Parallel Trends Assumption:

As discussed in Section 4.3.2, this estimator also requires parallel trends between the treatment and control groups in the absence of treatment. One way to check the validity of this is to look at the pre-treatment periods of the results. As seen in 4.13 the pre-treatment periods do not have statistically significant results. Thus, we can conclude that our parallel treatments assumption holds.

(2) No Anticipatory prior to treatment:

Again, as discussed in Section 4.3.2, this assumption holds since women would not change their behavior in anticipation of the RTE, but rather because of a change in household dynamics as a result of the child now going to school.

(3) Treatment Effect Homogeneity:

I briefly mention that assumption 3 (treatment effect homogeneity), does not hold in the context of my policy. However, the new estimator is robust to this assumption. Thus, my research design satisfies all the assumptions required for using the Callaway and SantAnna (2021) model.

Results

I next run the estimation using the package that accompanies Callaway and SantAnna (2021). My sample is the same as Section 4.3.1 where I have $77,788$ individuals and $59,882$ households across 3 different survey periods. Figure 4.13 shows us the coefficient plot of my estimation.

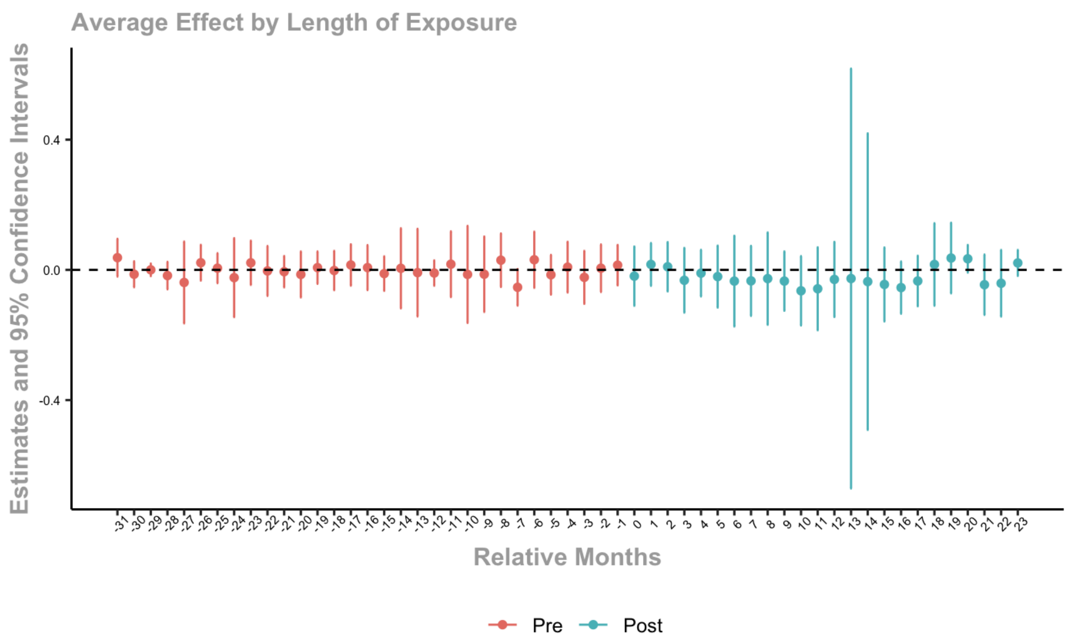

Figure 4.13: Coefficient Estimates without Control Variables

The graph above does not have a clear trend where I can measure a causal impact on the effects of the Right to Education Act on Female Labor Force Participation Rates. We again mostly see results that are not statistically significant. Moreover, there is no clear pattern that indicates a decline or increase in female labor force participation. Thus, we can conclude that the RTE's effect on mothers' labor force participation is mostly inconclusive when measured using the Santanna and Callaway Estimator.

Limitations of the Santanna and Callaway Estimator

As mentioned above, the results do not show statistically significant results. However, the model has many limitations and thus, may not be giving us the most accurate estimates. As mentioned earlier in Section 4.2, there are many other factors that govern womens decision to enter the labor force and these are not accounted for in the current model.

I was also unable to incorporate control variables in the Santanna and Callaway estimator because it involved statistics that are not user-friendly. The lack of control variables like education levels, and social groups could potentially be driving the trends behind the data which in turn could be leading to statistically insignificant results.

Moreover, the phased implementation nature of the policy makes it difficult to measure the causal impact in the long term because of the lack of a good counterfactual. Since all states get treated by 2012, it is not possible to draw a causal inference for time periods after that. Moreover, my theoretical model predicts that households may behave in completely different ways in response to the RTE, depending on how they are affected. My data, however, do not look only at households affected by the RTE, there are households who were probably affected by the SSA that I do not account for in my model. These effects could potentially be driving the statistically insignificant results.

There are also limitations in how my coefficient estimates are calculated. I rely on the replication package that may not be suited for the nature of my data. This in turn could be causing some sort of estimation bias. In future work, it is important to code these estimators that best suit the nature of the data to avoid such situations.

Discussion and Conclusion

5.1 Summary

My thesis seeks to answer the research question *"Did the Right to Education Act encourage female labor force participation?"*. I first use concepts from classical economic theory to develop a model that could explain different ways households could potentially behave. I build a unitary household model, and my predictions show that labor supply decisions could rise or fall depending on the household. Households whose time constraint relaxes because of free childcare will have a greater incentive to enter the labor force. On the other hand, households, where previously children did some household work, would have a negative effect on the time constraint. These households would in turn decrease their labor supply. On the other hand, the RTE can also be thought of as a conditional cash transfer because of free lunches, etc. On the other hand, the RTE could also induce additional costs (transportation, school bags, etc) for the household. If the policy relaxes the budget constraint, these households would reduce their labor supply, if instead, it increases costs it would increase their labor supply. Since my theoretical model, produces ambiguous results, I next use household survey data and econometrics techniques to empirically assess the effect of the RTE.

I use data from the Indian National Employment and Unemployment Surveys, for my analysis. I explore three different empirical techniques to test for causal inference. I first implement a simple canonical differences-in-differences model. My results indicate that my female labor force participation increases by 1.8% in states that were treated. While I get encouraging results, these results do not cover all states. This in turn could lead to misleading conclusions.

To overcome this constraint, I next implement a two-way fixed effects regression model with Staggered Timing. My results estimate no effect, but the model requires strong assumptions that I do not have in my experiment design. I overcome this limitation, by using an estimator that is robust to these assumptions. Thus, I use the estimator proposed by Callaway and SantAnna (2021) and conclude that the RTE did not have an effect on women's labor force participation across all states in India.

While I explore multiple techniques to test for the effect of the RTE on female labor force participation and find some encouraging signs, it is important to interpret the implications of my policy with great caution. My methods suffer from a lot of data and methodology constraints that I discuss in the next section.

5.2 Data and Methodology Constraints

In this section, I discuss some of the limitations my modeling techniques suffer from. One of the main constraints is the data. I do not have data beyond June 2012, which makes it hard to measure the long-term effect on female labor force participation. A woman could change her female labor force decisions in the long term in response to the RTE. The response may not be immediate as indicated in my model.

Moreover, the phased implementation nature of my policy roll-out can be thought of as an advantage and disadvantage. On one hand, it gives me not-yet-treated states to serve as counterfactual during the policy roll-out. On the other hand, the econometric techniques that could be used to overcome this have their limitations. Though new methods have been proposed for this kind of staggered implementation, not much is known about these methods. Thus, it is impossible to determine the accuracy of my results.

I use my theoretical model to guide my empirical model. However, my theoretical model provides a simple framework to think through mothers' labor force participation and has its' limitations in giving an accurate representation of the real world. For instance, my model uses a unitary household framework where I assume that a woman's labor force decisions are not influenced by other members of the household. This is an assumption that past literature argues could lead to misleading conclusions (Chiappori and Mazzocco 2017). Moreover, my theoretical model does not predict if a woman would enter the labor force but rather her aggregate labor supply which may not be answering my research question directly. Therefore, it is important to interpret the results of my study in context with these limitations.

5.3 Future Research:

I next discuss the implications of my results for policy-makers. Though my study does not find any effect of the RTE on female labor force participation throughout the country, it is important to note that there are some encouraging signs. Future research is required to estimate the impact across all states in India.

My study also sheds light that it is important to study factors that would increase female labor force participation rates in India. Specifically, it is important to examine ways to relax other constraints such as d gender norms, safety for women in the workplace, wage disparity, etc., which could be holding women back. Thus, it is important to examine different factors and policies that could encourage higher female labor force participation.

It is also important to perform robustness checks for my model. For instance, as mentioned in Section 2.1, the RTE closed schools that did not have proper documentation. Thus, it is important to check if this reduced accessibility to schools in turn could be resulting in statistically insignificant results. Another important robustness check could potentially be comparing how the RTE impacts mothers in treated states with non-mothers in those states. This will help overcome some of the limitations I face with defining my counterfactual for this study.

Another possible area of research is examining the effect of free childcare in different contexts rather than just primary school education. Other factors like preschool education system could perhaps encourage more young women to enter the labor force. Other empirical techniques like RCTs, etc may also perhaps be able to give us a better idea of the effect of free childcare on mothers' labor force participation decisions.

Bibliography

Agénor, Pierre-Richard, and Otaviano Canuto. 2015. "Gender equality and economic growth in Brazil: A long-run analysis" [in en]. *Journal of Macroeconomics* 43 (March): 155–172. ISSN: 0164-0704, accessed March 25, 2023. https://doi.org/10.1016/j.jmacro.2014.10.004. https://www.sciencedirect.com/science/article/pii/S0164070414001189.

Alesina, Alberto, Paola Giuliano, and Nathan Nunn. 2013. "On the Origins of Gender Roles: Women and the Plough*" [in en]. *The Quarterly Journal of Economics* 128, no. 2 (May): 469–530. ISSN: 0033-5533, 1531-4650, accessed March 31, 2023. https://doi.org/10.1093/qje/qjt005. https://academic.oup.com/qje/article/128/2/469/1943509.

Anderson, Siwan, and Mukesh Eswaran. 2009. "What determines female autonomy? Evidence from Bangladesh" [in en]. *Journal of Development Economics* 90, no. 2 (November): 179–191. ISSN: 03043878, accessed April 2, 2023. https://doi.org/10.1016/j.jdeveco.2008.10.004. https://linkinghub.elsevier.com/retrieve/pii/S0304387808001089.

Bandiera, Oriana, Niklas Buehren, Robin Burgess, Markus Goldstein, Selim Gulesci, Imran Rasul, and Munshi Sulaiman. 2020. "Womens Empowerment in Action: Evidence from a Randomized Control Trial in Africa" [in en]. *American Economic Journal: Applied Economics* 12, no. 1 (January): 210–259. ISSN: 1945-7782, 1945-7790, accessed April 2, 2023. https://doi.org/10.1257/app.20170416. https://pubs.aeaweb.org/doi/10.1257/app.20170416.

Bandura, Albert, Claudio Barbaranelli, Gian Vittorio Caprara, and Concetta Pastorelli. 2001. "Self-Efficacy Beliefs as Shapers of Children's Aspirations and Career Trajectories" [in en]. *Child Development* 72, no. 1 (January): 187–206. ISSN: 0009-3920, 1467-8624, accessed March 31, 2023. https://doi.org/10.1111/1467-8624.00273. https://onlinelibrary.wiley.com/doi/10.1111/1467-8624.00273.

Beaman, Lori, Esther Duflo, Rohini Pande, and Petia Topalova. 2012. "Female Leadership Raises Aspirations and Educational Attainment for Girls: A Policy Experiment in India" [in en]. *Science* 335, no. 6068 (February): 582–586. ISSN: 0036-8075, 1095-9203, accessed March 31, 2023. https://doi.org/10.1126/science.1212382. https://www.science.org/doi/10.1126/science.1212382.

Becker, Gary S. 1965. "A Theory of the Allocation of Time." *The Economic Journal* 75, no. 299 (September): 493. ISSN: 00130133, accessed April 2, 2023. https://doi.org/10.2307/2228949. https://academic.oup.com/ej/article/75/299/493-517/5250146.

Bick, Alexander. 2016. "THE QUANTITATIVE ROLE OF CHILD CARE FOR FEMALE LABOR FORCE PARTICIPATION AND FERTILITY: The Quantitative Role of Child Care" [in en]. *Journal of the European Economic Association* 14, no. 3 (June): 639–668. ISSN: 15424766, accessed April 1, 2023. https://doi.org/10.1111/jeea.12143. https://academic.oup.com/jeea/article-lookup/doi/10.1111/jeea.12143.

Blundell, Richard, PierreAndré Chiappori, and Costas Meghir. 2005. "Collective Labor Supply with Children" [in en]. *Journal of Political Economy* 113, no. 6 (December): 1277–1306. ISSN: 0022-3808, 1537-534X, accessed April 2, 2023. https://doi.org/10.1086/491589. https://www.journals.uchicago.edu/doi/10.1086/491589.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2021. "Revisiting Event Study Designs: Robust and Efficient Estimation." Publisher: arXiv Version Number: 2, accessed December 20, 2022. https://doi.org/10.48550/ARXIV.2108.12419. https://arxiv.org/abs/2108.12419.

Bose, Nayana, and Shreyasee Das. 2017. "Women's Inheritance Rights, Household Allocation, and Gender Bias" [in en]. *American Economic Review* 107, no. 5 (May): 150–153. ISSN: 0002-8282, accessed February 20, 2023. https://doi.org/10.1257/aer.p20171128. https://pubs.aeaweb.org/doi/10.1257/aer.p20171128.

Brander, James A., and Steve Dowrick. 1994. "The role of fertility and population in economic growth: Empirical results from aggregate cross-national data" [in en]. *Journal of Population Economics* 7, no. 1 (February): 1–25. ISSN: 0933-1433, 1432-1475, accessed February 20, 2023. https://doi.org/10.1007/BF00160435. http://link.springer.com/10.1007/BF00160435.

Callaway, Brantly, and Pedro H. C. SantAnna. 2021. "Difference-in-Differences with multiple time periods" [in en]. *Journal of Econometrics,* Themed Issue: Treatment Effect 1, 225, no. 2 (December): 200–230. ISSN: 0304-4076, accessed February 15, 2023. https://doi.org/10.1016/j.jeconom.2020.12.001. https://www.sciencedirect.com/science/article/pii/S0304407620303948.

Carranza, Eliana. 2014. "Soil Endowments, Female Labor Force Participation, and the Demographic Deficit of Women in India" [in en]. *American Economic Journal: Applied Economics* 6, no. 4 (October): 197–225. ISSN: 1945-7782, 1945-7790, accessed April 1, 2023. https://doi.org/10.1257/app.6.4.197. https://pubs.aeaweb.org/doi/10.1257/app.6.4.197.

Cherchye, Laurens, Bram De Rock, and Frederic Vermeulen. 2012. "Married with Children: A Collective Labor Supply Model with Detailed Time Use and Intrahousehold Expenditure Information" [in en]. *American Economic Review* 102, no. 7 (December): 3377–3405. ISSN: 0002-8282, accessed December 20, 2022. https://doi.org/10.1257/aer.102.7.3377. https://pubs.aeaweb.org/doi/10.1257/aer.102.7.3377.

Chiappori, Pierre-André. 1992. "Collective Labor Supply and Welfare" [in en]. *Journal of Political Economy* 100, no. 3 (June): 437–467. ISSN: 0022-3808, 1537-534X, accessed April 2, 2023. https://doi.org/10.1086/261825. https://www.journals.uchicago.edu/doi/10.1086/261825.

———. 1997. "Introducing Household Production in Collective Models of Labor Supply" [in en]. *Journal of Political Economy* 105, no. 1 (February): 191–209. ISSN: 0022-3808, 1537-534X, accessed April 2, 2023. https://doi.org/10.1086/262071. https://www.journals.uchicago.edu/doi/10.1086/262071.

Chiappori, Pierre-Andre, and Maurizio Mazzocco. 2017. "Static and Intertemporal Household Decisions" [in en]. *Journal of Economic Literature* 55, no. 3 (September): 985–1045. ISSN: 0022-0515, accessed February 22, 2023. https://doi.org/10.1257/jel.20150715. https://pubs.aeaweb.org/doi/10.1257/jel.20150715.

Compton, Janice, and Robert A. Pollak. 2014. "Family proximity, childcare, and womens labor force attachment" [in en]. *Journal of Urban Economics* 79 (January): 72–90. ISSN: 00941190, accessed February 20, 2023. https://doi.org/10.1016/j.jue.2013.03.007. https://linkinghub.elsevier.com/retrieve/pii/S0094119013000314.

Connelly, Rachel. 1992. "The Effect of Child Care Costs on Married Women's Labor Force Participation." *The Review of Economics and Statistics* 74, no. 1 (February): 83. ISSN: 00346535, accessed March 25, 2023. https://doi.org/10.2307/2109545. https://www.jstor.org/stable/2109545?origin=crossref.

Esteve-Volart, Berta. 2004. *Gender Discrimination and Growth: Theory and Evidence from India.* STICERD - Development Economics Papers - From 2008 this series has been superseded by Economic Organisation and Public Policy Discussion Paper. Suntory, Toyota International Centres for Economics, and Related Disciplines, LSE, January. Accessed March 25, 2023. https://econpapers.repec.org/paper/cepstidep/42.htm.

Fernandez, R., A. Fogli, and C. Olivetti. 2004. "Mothers and Sons: Preference Formation and Female Labor Force Dynamics" [in en]. *The Quarterly Journal of Economics* 119, no. 4 (November): 1249–1299. ISSN: 0033-5533, 1531-4650, accessed April 1, 2023. https://doi.org/10.1162/0033553042476224. https://academic.oup.com/qje/article-lookup/doi/10.1162/0033553042476224.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing" [in en]. *Journal of Econometrics* 225, no. 2 (December): 254–277.

ISSN: 03044076, accessed March 9, 2023. https://doi.org/10.1016/j.jeconom.2021.03.014. https://linkinghub.elsevier.com/retrieve/pii/S0304407621001445.

Heath, Rachel. 2014. "Womens Access to Labor Market Opportunities, Control of Household Resources, and Domestic Violence: Evidence from Bangladesh" [in en]. *World Development* 57 (May): 32–46. ISSN: 0305750X, accessed December 5, 2022. https://doi.org/10.1016/j.worlddev.2013.10.028. https://linkinghub.elsevier.com/retrieve/pii/S0305750X13002404.

Jayachandran, Seema. 2015. "The Roots of Gender Inequality in Developing Countries" [in en]. *Annual Review of Economics* 7, no. 1 (August): 63–88. ISSN: 1941-1383, 1941-1391, accessed March 31, 2023. https://doi.org/10.1146/annurev-economics-080614-115404. https://www.annualreviews.org/doi/10.1146/annurev-economics-080614-115404.

Lee, Grace H.Y., and Sing Ping Lee. 2014. "Childcare availability, fertility and female labor force participation in Japan" [in en]. *Journal of the Japanese and International Economies* 32 (June): 71–85. ISSN: 08891583, accessed December 5, 2022. https://doi.org/10.1016/j.jjie.2014.01.002. https://linkinghub.elsevier.com/retrieve/pii/S088915831400015X.

Mathew, Shalina Susan. 2015. "Falling female labour force participation in Kerala: Empirical evidence of discouragement?" [In en]. *International Labour Review* 154, no. 4 (December): 497–518. ISSN: 00207780, accessed April 1, 2023. https://doi.org/10.1111/j.1564-913X.2015.00251.x. https://onlinelibrary.wiley.com/doi/10.1111/j.1564-913X.2015.00251.x.

Mazzocco, Maurizio. 2007. "Household Intertemporal Behaviour: A Collective Characterization and a Test of Commitment" [in en]. *The Review of Economic Studies* 74, no. 3 (July): 857–895. ISSN: 1467-937X, 0034-6527, accessed April 2, 2023. https://doi.org/10.1111/j.1467-937X.2007.00447.x. https://academic.oup.com/restud/article-lookup/doi/10.1111/j.1467-937X.2007.00447.x.

Mehrotra, Santosh, and Jajati K. Parida. 2017. "Why is the Labour Force Participation of Women Declining in India?" [In en]. *World Development* 98 (October): 360–380. ISSN: 0305750X, accessed March 31, 2023. https://doi.org/10.1016/j.worlddev.2017.05.003. https://linkinghub.elsevier.com/retrieve/pii/S0305750X17301663.

Mishra, Ankita, Vinod Mishra, and Jaai Parasnis. 2021. "The asymmetric role of crime in women's and men's labour force participation: Evidence from India" [in en]. *Journal of Economic Behavior & Organization* 188 (August): 933–961. ISSN: 01672681, accessed April 2, 2023. https://doi.org/10.1016/j.jebo.2021.06.015. https://linkinghub.elsevier.com/retrieve/pii/S0167268121002481.

Ranganathan, Aruna, and David S. Pedulla. 2021. "Work-Family Programs and Nonwork Networks: Within-Group Inequality, Network Activation, and Labor Market Attachment" [in en]. *Organization Science* 32, no. 2 (March): 315–333. ISSN: 1047-7039, 1526-5455, accessed December 5, 2022. https://doi.org/10.1287/orsc.2020.1391. http://pubsonline.informs.org/doi/10.1287/orsc.2020.1391.

Rosenzweig, Mark R., and T. Paul Schultz. 1982. "Market Opportunities, Genetic Endowments, and Intrafamily Resource Distribution: Child Survival in Rural India." Publisher: American Economic Association, *The American Economic Review* 72 (4): 803–815. ISSN: 0002-8282, accessed April 2, 2023. https://www.jstor.org/stable/1810018.

Roth, Jonathan, Pedro H. C. Sant'Anna, Alyssa Bilinski, and John Poe. 2022. "What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature." Publisher: arXiv Version Number: 3, accessed March 31, 2023. https://doi.org/10.48550/ARXIV.2201.01194. https://arxiv.org/abs/2201.01194.

Shah, Manisha, and Bryce Steinberg. 2019. "The Right to Education Act: Trends in Enrollment, Test Scores, and School Quality" [in en]. *AEA Papers and Proceedings* 109 (May): 232–238. ISSN: 2574-0768, 2574-0776, accessed February 20,

2023. https://doi.org/10.1257/pandp.20191060. https://pubs.aeaweb.org/doi/10.1257/pandp.20191060.

Singh, Inderjit, Lyn Squire, John Strauss, and World Bank, eds. 1986. *Agricultural household models: extensions, applications, and policy.* A World Bank research publication. Baltimore: Johns Hopkins University Press. ISBN: 978-0-8018-3149-2.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects" [in en]. *Journal of Econometrics,* Themed Issue: Treatment Effect 1, 225, no. 2 (December): 175–199. ISSN: 0304-4076, accessed February 8, 2023. https://doi.org/10.1016/j.jeconom.2020.09.006. https://www.sciencedirect.com/science/article/pii/S030440762030378X.

Verick, Ruchika Chaudhary and Sher. 2014. *Female labour force participation in India and beyond* [in en]. Working paper. ISSN: 2227-4405. October. Accessed February 20, 2023. http://www.ilo.org/newdelhi/whatwedo/publications/WCMS_324621/lang--en/index.htm.

Yadav, S. K., Radhey Shyam Sharma, and Marshal Birua. 2018. "Sarva Shiksha Abhiyan: Achievements, Problems and Future Prospects: A Comparative Analysis of Some Indian States" [in en]. In *Reflecting on Indias Development: Employment, Skill and Health,* edited by NILERD, 175–201. Singapore: Springer. ISBN: 9789811314148, accessed March 14, 2023. https://doi.org/10.1007/978-981-13-1414-8_9. https://doi.org/10.1007/978-981-13-1414-8_9.

Appendix

A.1 Coefficient Table from the Two-Way Fixed Effects Regression

Dependent Variable:	Female Labor Force Participation
treated$_{s}tates \times relative_months = -33$	0.0292
	(0.0473)
treated_states × relative_months = -32	-0.0702
	(0.0487)
treated_states × relative_months = -31	-0.0278
	(0.0507)
treated_states × relative_months = -30	-0.0330
	(0.0458)
treated_states × relative_months = -29	-0.0141
	(0.0514)
treated_states × relative_months = -28	-0.0207
	(0.0535)
treated_states × relative_months = -27	-0.0415
	(0.0414)
treated_states × relative_months = -26	-0.0262
	(0.0372)
treated_states × relative_months = -25	-0.0119
	(0.0348)
treated_states × relative_months = -24	-0.0281
	(0.0369)
treated_states × relative_months = -23	-0.0241
	(0.0382)
treated_states × relative_months = -22	-0.0394
	(0.0415)
treated_states × relative_months = -21	-0.0151
	(0.0369)
treated_states × relative_months = -20	-0.0297
	(0.0346)
treated_states × relative_months = -19	-0.0403
	(0.0299)
treated_states × relative_months = -18	-0.0454
	(0.0302)
treated_states × relative_months = -17	-0.0323
	(0.0333)
treated_states × relative_months = -16	-0.0372
	(0.0306)
treated_states × relative_months = -15	-0.0253
	(0.0362)
treated_states × relative_months = -14	-0.0138

	(0.0258)
treated_states × relative_months = -13	-0.0236
	(0.0272)
treated_states × relative_months = -12	-0.0204
	(0.0261)
treated_states × relative_months = -11	-0.0223
	(0.0236)
treated_states × relative_months = -10	-0.0234
	(0.0269)
treated_states × relative_months = -9	-0.0306
	(0.0243)
treated_states × relative_months = -8	-0.0019
	(0.0196)
treated_states × relative_months = -7	-0.0328
	(0.0196)
treated_states × relative_months = -6	-0.0139
	(0.0195)
treated_states × relative_months = -5	-0.0302
	(0.0182)
treated_states × relative_months = -4	-0.0092
	(0.0148)
treated_states × relative_months = -3	-0.0123
	(0.0177)
treated_states × relative_months = -2	-0.0043
	(0.0135)
treated_states × relative_months = 0	-0.0314**
	(0.0149)
treated_states × relative_months = 1	-0.0101
	(0.0138)
treated_states × relative_months = 2	-0.0036
	(0.0124)
treated_states × relative_months = 3	-0.0182
	(0.0130)
treated_states × relative_months = 4	-0.0119
	(0.0160)
treated_states × relative_months = 5	-0.0393***
	(0.0111)
treated_states × relative_months = 6	-0.0234*
	(0.0137)
treated_states × relative_months = 7	-0.0274*
	(0.0145)
treated_states × relative_months = 8	-0.0123
	(0.0176)
treated_states × relative_months = 9	0.0022
	(0.0192)
treated_states × relative_months = 10	-0.0219
	(0.0169)
treated_states × relative_months = 11	-0.0029
	(0.0143)
treated_states × relative_months = 12	-0.0054
	(0.0200)
treated_states × relative_months = 13	0.0064
	(0.0164)
treated_states × relative_months = 14	0.0006
	(0.0213)
treated_states × relative_months = 15	-0.0051
	(0.0183)
treated_states × relative_months = 16	-0.0096

	(0.0130)
treated_states × relative_months = 17	0.0017
	(0.0221)
treated_states × relative_months = 18	0.0206
	(0.0218)
treated_states × relative_months = 19	0.0159
	(0.0216)
treated_states × relative_months = 20	0.0159
	(0.0249)
treated_states × relative_months = 21	-0.0086
	(0.0178)
treated_states × relative_months = 22	0.0124
	(0.0174)
treated_states × relative_months = 23	0.0257
	(0.0290)
treated_states × relative_months = 24	0.0191
	(0.0187)
treated_states × relative_months = 25	0.0052
	(0.0156)
college_education	0.0659***
	(0.0160)
married	-0.2331***
	(0.0163)
Fixed-effects	
State	Yes
Month	Yes
Fit statistics	
Observations	77,780
R^2	0.07569
Within R^2	0.03323

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.2 Coefficient Table from the Santanna and Callaway Estimator:

Time	Estimate	Std.Error	Conf.Low	Conf.High	Point.Conf.Low	Point.Conf.High
-31	0.04	0.02	-0.02	0.10	-0.00	0.08
-30	-0.01	0.01	-0.05	0.03	-0.04	0.02
-29	0.00	0.01	-0.02	0.02	-0.01	0.01
-28	-0.02	0.02	-0.06	0.02	-0.05	0.01
-27	-0.04	0.05	-0.16	0.09	-0.13	0.05
-26	0.02	0.02	-0.03	0.08	-0.02	0.06
-25	0.01	0.02	-0.04	0.05	-0.03	0.04
-24	-0.02	0.04	-0.14	0.10	-0.11	0.06
-23	0.02	0.02	-0.05	0.09	-0.03	0.07
-22	-0.00	0.03	-0.08	0.07	-0.06	0.05
-21	-0.01	0.02	-0.05	0.04	-0.04	0.03
-20	-0.01	0.03	-0.08	0.06	-0.06	0.04
-19	0.01	0.02	-0.04	0.06	-0.03	0.04
-18	-0.00	0.02	-0.06	0.06	-0.05	0.04
-17	0.02	0.02	-0.05	0.08	-0.03	0.06
-16	0.01	0.03	-0.06	0.08	-0.04	0.06
-15	-0.01	0.02	-0.06	0.04	-0.05	0.03
-14	0.00	0.05	-0.12	0.13	-0.08	0.09
-13	-0.01	0.05	-0.14	0.13	-0.11	0.09
-12	-0.01	0.01	-0.05	0.03	-0.04	0.02
-11	0.02	0.04	-0.08	0.12	-0.06	0.09
-10	-0.01	0.05	-0.16	0.14	-0.12	0.09
-9	-0.01	0.04	-0.13	0.10	-0.10	0.07
-8	0.03	0.03	-0.05	0.11	-0.03	0.09
-7	-0.05	0.02	-0.11	0.00	-0.09	-0.01
-6	0.03	0.03	-0.06	0.12	-0.03	0.09
-5	-0.02	0.02	-0.08	0.05	-0.06	0.03
-4	0.01	0.03	-0.07	0.09	-0.05	0.06
-3	-0.02	0.03	-0.10	0.06	-0.08	0.04
-2	0.01	0.03	-0.07	0.08	-0.05	0.06
-1	0.01	0.02	-0.05	0.08	-0.03	0.06
0	-0.02	0.03	-0.11	0.07	-0.08	0.05
1	0.02	0.02	-0.05	0.08	-0.03	0.06
2	0.01	0.03	-0.07	0.09	-0.05	0.06
3	-0.03	0.04	-0.13	0.07	-0.10	0.04

4	-0.01	0.03	-0.08	0.06	-0.06	0.04
5	-0.02	0.04	-0.12	0.07	-0.09	0.05
6	-0.03	0.05	-0.17	0.10	-0.14	0.07
7	-0.03	0.04	-0.14	0.07	-0.11	0.04
8	-0.03	0.05	-0.17	0.11	-0.13	0.08
9	-0.03	0.03	-0.13	0.06	-0.10	0.03
10	-0.06	0.04	-0.17	0.04	-0.14	0.01
11	-0.06	0.05	-0.19	0.07	-0.15	0.03
12	-0.03	0.04	-0.14	0.09	-0.11	0.05
13	-0.03	0.24	-0.67	0.62	-0.49	0.44
14	-0.04	0.17	-0.49	0.42	-0.37	0.29
15	-0.04	0.04	-0.16	0.07	-0.13	0.04
16	-0.05	0.03	-0.13	0.03	-0.11	0.00
17	-0.03	0.03	-0.11	0.04	-0.09	0.02
18	0.02	0.05	-0.11	0.14	-0.07	0.11
19	0.04	0.04	-0.07	0.14	-0.04	0.11
20	0.03	0.02	-0.01	0.08	0.00	0.06
21	-0.05	0.03	-0.14	0.05	-0.11	0.02
22	-0.04	0.04	-0.14	0.06	-0.11	0.03
23	0.02	0.01	-0.02	0.06	-0.01	0.05