Mother's Education and Child Nutrition: Evidence of Intergenerational Effect from a School Cycle Program, India

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Abstract

We study the intergenerational effect, channeled through mothers' education, of a school cycle program targeting girls enrolled in class nine on child nutrition outcomes in the Indian state of Bihar. Utilizing nationally representative individual-level data, our difference-in-difference estimates demonstrate that the nutritional status of children whose mothers were exposed to the program has improved significantly. The children of treated mothers are 4.1 and 2.3 percentage points less likely to be stunted and underweight, respectively. The observed positive effects are plausibly driven by increased maternal educational attainments, higher income levels, declined fertility, increased birth-interval, and media exposures, and improved access to maternal and child health services. The heterogeneity analysis indicates that the effects are greater in upper castes and wealthier households and more pronounced for male children.

JEL classification: H52, I10, I16, I28

Keywords: Cycle program, intergenerational, child nutrition, education, Bihar, India

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1. Introduction

Nutrition status of children is one of the key determinants of economic development as their health is associated with later economic and life outcomes such as adult health, productivity, and income (Victora et al., 2008). Though India is the fifth largest economy in the world, its nutrition status is alarming as the country ranks 105th out of 127 countries as per the Global Hunger Index, 2024[3]. Bihar, one of India's poor-performing states in terms of economic and development indicators, bears a disproportionately heavy burden of child malnutrition, with 43% of children stunted and 23% wasted[4]. The government of India, in collaboration with the state governments, has introduced several programs including Mid-day meal and Public Distribution System to address malnutrition through improvement in food security across the country. However, the focus on initiatives indirectly affecting nutrition has been limited. One of the strongest predictors of child health is mother's education as an educated mother has better knowledge of health care and nutrition (Chen & Li, 2009). In this study, we investigate how an in-kind conditional transfer program focused on increasing girls' enrolment in secondary schools improves the nutrition outcomes of their children.

Specifically, we investigate the intergenerational effect of a cycle program on child nutrition outcomes, channeled through mother's education. With the stated goals of increasing girls' school enrolment rate and minimizing their school dropout by making it easier for them to access school, the state government of Bihar in 2006 introduced the cycle program, namely, Mukhyamantri Balika Cycle Yojana (hereafter, cycle program). Its objective was to decrease girl's school dropout rates in Bihar, by making it easier for them to access school. We consider the girls who have passed their senior secondary examination before 2006 or dropped out of school after primary schooling (who were not eligible to get program benefits) as the control group whereas the younger girls supposed to enter class 9 in 2006 or later, as the treatment group. Since the program was implemented only in the state of Bihar in 2006, we use Jharkhand and Uttar Pradesh as the control states[5]. This allows us to exploit the state and cohort variation to estimate the causal effect using difference-in-differences technique. We use data from the National Family Health Survey, round-4 conducted in year 2015-16, which provides rich

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[3] Wiemers, M., Bachmeier, M., Hanano, A., Cheilleachair. N. R., Vaughan, A., Foley, C., Mann, H., Weller, D., Radtke, K., Fritschel, H. (2024). Global Hunger Index: How Gender Justice Can Advance Climate Resilience and Zero Hunger. https://www.globalhungerindex.org/pdf/en/2024.pdf

[4] International Institute for Population Sciences (IIPS) and ICF, (2022). Fact sheet: key indicators from Phase-1, National Family Health Survey (NFHS-5). https://mohfw.gov.in/sites/default/files/NFHS-5_Phase-I.pdf

[5]These states have geographical and cultural proximity to Bihar, and they do not have any such program in the year 2006 or later (Kjelsrud et al., 2024).

information on several demographic and socioeconomic characteristics of ever-married women, aged 15-49, along with their fertility history and child health and nutrition outcomes.

Our study makes two contributions to literature. Firstly, our study adds to the existing literature on the differential effects of a cycle program by studying the intergenerational spillover effects. The existing literature has studied the program's coverage rate and its effect on secondary school enrolment of girls and their empowerment in addition to spillover effects on non-targeted females (Fiala et al., 2022; Ghatak et al., 2016; Kjelsrud et al., 2024; Mitra & Moene, 2017; Muralidharan & Prakash, 2017). Ghatak et al. (2016) studied the performance of the program and found that beneficiaries favor in-kind transfer instead of cash, and the program performed well in terms of covering the beneficiaries. Muralidharan & Prakash (2017), using a triple difference technique to exploit the variation within state and age cohorts and analyzing the potential mechanism, demonstrated that the program not only increased the secondary school enrolment among girls but also reduced the gender gap in age-appropriate secondary school enrolment by 40%. Mitra & Moene (2017) pointed out that social transfer has long-term effect on the aspirations of the girls, by impacting their occupation choice. This later translates into increasing the power of intrahousehold decision-making not just for themselves, but also for older women residing with them due to intra-household effects (Kjelsrud et al., 2024). A similar study in Zambia found evidence of a bicycle program improving attendance and test scores for girls and empowering the girls with control over their lives and delaying marriage and pregnancy in future (Fiala et al., 2022). All these studies analyzed the impact of school cycle programs on intended beneficiaries and women living with them; however, there a is dearth of studies that evaluate their effect on the children of girls. To the best of our knowledge, our study is the first to assess the intergenerational effect of an in-kind transfer program, channeled through mother's education.

Secondly, this study contributes to a large and growing body of literature on the relationship between mother's education and their children's education and health outcomes. A few studies have investigated the impact of maternal education on their fertility decisions and child health outcomes through changes in the country's educational reform, and reported mixed results (Arendt at al., 2021; Cygan-Rehm & Maeder, 2013; Gunes, 2015; Keats, 2018; Kemptner et al., 2011; Le & Nguyen, 2020; Lindeboom et al., 2009). Currie & Moretti (2011) found that additional years of college education for mothers improve infant health, measured through birth weight and gestational age. Gunes (2015), studying the compulsory schooling program and construction of additional classrooms in Turkey, found that mother's primary schooling improves the birth weight, weight-for-age z-scores and height-for-age z-scores of children under the age of five. Keats (2018) demonstrated that through the elimination of primary school fees reform in Uganda, educated mothers are more likely to reduce fertility, delay pregnancy, have less malnourished children and increase early life child health intervention. In contrast to the existing studies, Lindeboom et al. (2009) found that an increase in parental education with schooling reform in the UK had little effect on child health outcomes as education did not necessarily affect parental health and behavior. Similarly, Arendt at al. (2021) revealed that the minimum compulsory schooling reform in Denmark had positive effects on maternal health and their age at birth but no effect on child health outcomes. A vast body of literature presents mixed findings regarding the relationship between mothers' education and child health and nutrition, predominantly derived from studies conducted in developed countries. Hence, our study adds to the existing literature by establishing a causal link between maternal education and children nutrition outcomes in a resource-poor country setting by instrumenting through the Bihar Cycle Program. We also investigate the potential mechanisms driving our results.

We found that the program has positive effects for the children of mothers benefited through the cycle program. Their nutritional health outcomes have improved significantly. A child born to a mother exposed to the program is less likely to be stunted and underweight. Potential channels underlying these favorable effects include an increase in the mother's years of education, attainment of secondary level education, greater income status, improved access to maternal and child healthcare services, declined fertility, increased birth interval, and enhanced exposure to media such as newspapers, radio, and the internet.

We organize the rest of the paper as follows: Section 2 presents context of the Bihar cycle program and conceptual framework, Section 3 describes the data, empirical strategy and identification assumption. Section 4 presents the main results and the potential mechanisms, and section 5 concludes.

2. Context

2.1. The Bicycle Program in Bihar

Bihar, with a population of more than 100 million is one of the poorest and backward states of India. In early 2000, the literacy rate in Bihar was 47.5 % significantly below the country's average. The situation was even more concerning for women, with the female literacy rate at only 33.5%, highlighting deep gender disparities in access to education (Census of India, 2001). The dropout rate from school was pronounced among girls specifically those entering secondary level of education due to distant secondary schools. In 2006, the Mukhyamanri Balika Cycle Yojana was introduced in Bihar to improve the girl's enrollment rate by improving access to school. The program provides money to all the girls enrolled in class/standard 9 in a government-aided school. Initially, a fund of INR 2000 was provided to schoolgirls to purchase the bicycle, which was revised to Rs 2500 in 2009-10, and boys were also included under the program. The funds were distributed to eligible girls during public ceremonies organized in schools and were conditional upon the submission of bicycle purchase receipt to the school authorities which increase social awareness and accountability (Ghatak et al., 2016). In 2012-13, an additional condition of minimum 75% school attendance was also imposed to receive the funds.

Evidence suggests that the program was implemented well as 98% of the households purchased bicycles using program money, with only 3% of household did not get benefit despite fulfilling eligibility criteria, and only 2% of the beneficiaries did not purchase the bicycle after receiving cash transfer (Ghatak et al., 2016). These data are based on the large household survey conducted in 2012 among the beneficiaries of the program which revealed that most of them were satisfied with the program. The program became popular and succeeded in increasing secondary school enrollment for girls due to its political backing, no discretion by the implementing authorities, and collective pressure by beneficiaries on school authorities for timely transfer (Mitra & Moene, 2017).

2.2. Conceptual framework

Based on the evidence from several low-and-middle-income countries, we have developed a conceptual framework that outlines the potential pathways, broken down in two stages, that the cycle program could take to improve the child nutrition outcomes (Figure 1). The first stage documents that the cycle program would increase school enrollment for girls, along with a decline in dropout rates. Their school attendance would also improve as the cycle would reduce not only the daily cost of travelling but also the travelling time. Together, these would contribute to an increase in the educational attainment of girls who benefitted from the program (Muralidharan & Prakash, 2017). Since programs targeting girls' education may have some effects on future generations, we hypothesize that in the second stage, an increased education level gained through the cycle program would influence the nutritional health outcomes of their children through three primary pathways:

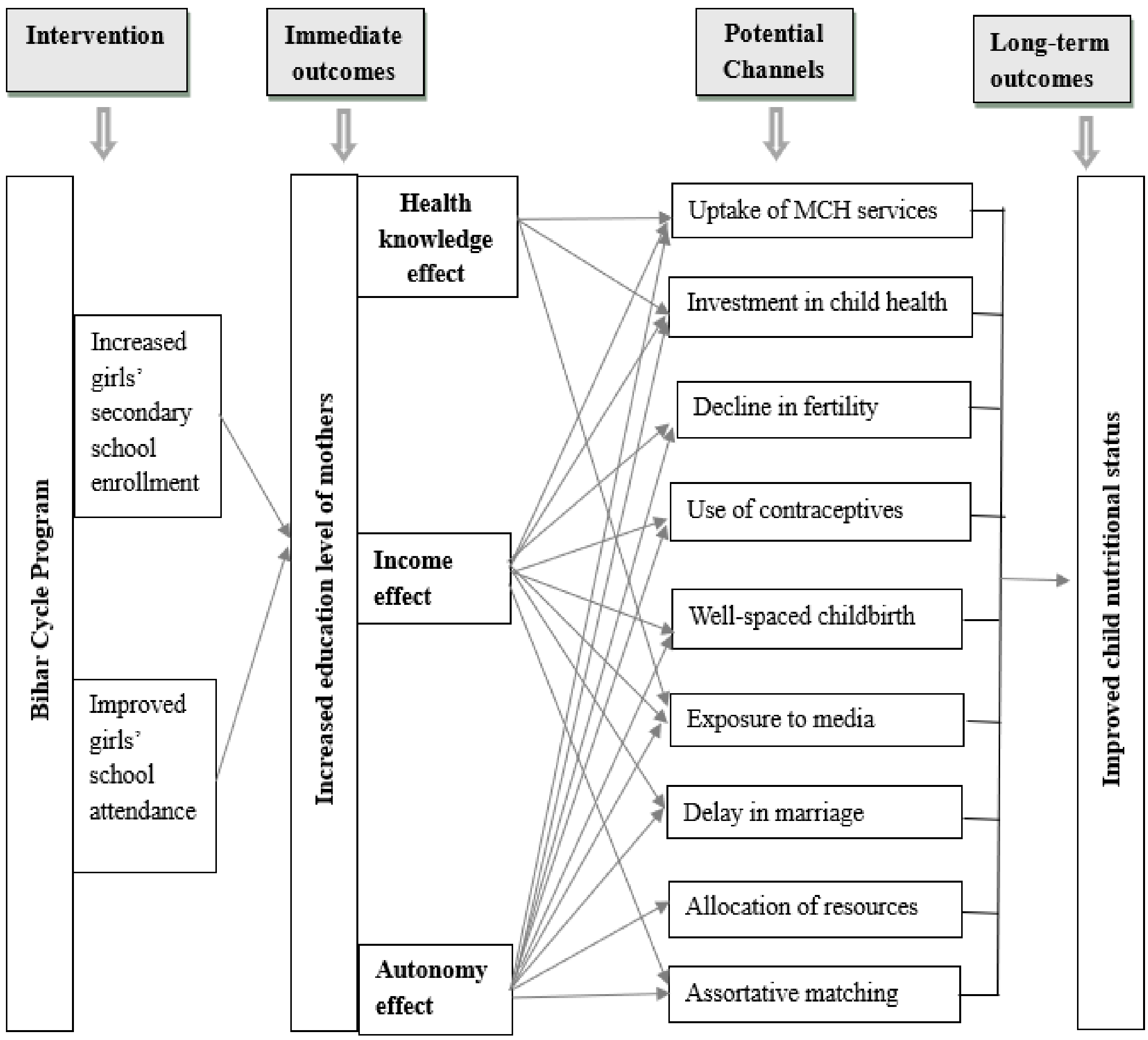
2.2.1. Health knowledge effect: The relationship between schooling and health is based on the productive efficiency theory in the context of demand for health (Grossman, 2008). The demand for health for mothers and their children will increase in the long term, as educated individuals are efficient health producers (Grossman, 1972). The allocative efficiency hypothesis suggests that a more educated person chooses a combination of inputs that produce more output than the ones chosen by their less educated counterparts (Altindag et al., 2011; Grossman, 2008). This model was extended further by considering families as the producer of health, and it was found that educated parents invest more in the health and nutrition of their children (Jacobson, 2000). Educated mothers have better health knowledge and awareness of nutrition, hygiene, modern health services, and preventive and risky health behaviors, which would help them make informed decisions and health investments at different phases of early child development (Prickett & Augustine, 2016). Education enhances their health knowledge and equips them to use mass media, which would further improve their children's health (Burchi, 2010). They are more likely to utilize maternal and child health services such as prenatal, natal, and postnatal care, leading to better health outcomes.

2.2.2. Income effect: Schooling raises household income through mothers' participation in the labor force, and higher wages due to increased productivity (Glewwe Paul, 1999). Increased income of the household would enhance the health and nutrition of their children with an increase in purchasing power, thus breaking the vicious intergenerational cycle of poverty and malnutrition. An educated mother will have a better standard of living, which would lead to increased consumption of nutritious food by mothers and children, which in turn would improve child nutrition. We can also attribute the increased income effect to marriage with an educated and high-income partner (Currie & Moretti, 2011; Gunes, 2015). As laid out in the quantity-quality trade-off model of Becker & Lewis (1973), an increase in income will increase the demand for high-quality children and decrease the demand for the quantity of children. It will result in a decline in the number of children, increased use of contraceptives, investment in children's health and nutrition, and access to services.

2.2.3. Autonomy effect: Women empowerment plays a major role in their reproductive health behavior, including utilization of maternal and child health services, and improvement in child nutrition (Aslam & Kingdon 2012). Maternal education is associated with increased bargaining power among mothers in the household, enhancing their mobility, and control over the household resources (Cui et al., 2019). It endows them with knowledge and power to make decisions regarding their marriage, fertility, contraceptives use, reproductive health practices, and children's human capital investment, all of which would, in turn, enhance child well-being (Chari et al., 2017; Samkaroon & Parinduri, 2015). Educated and empowered women enter late in the marriage market, which affects their age at marriage and fertility behavior, leading to reduction in the incidence of teenage pregnancy (Black et.al., 2008; Grepin & Bharadwaj, 2015; Gunes, 2015; Keats, 2018; Rehm and Maeder, 2013). Delayed pregnancy with well-spaced childbirths reduces the health risk for both mothers and children, thus contributing to the improvement in nutritional outcomes of children (Adediran, 2024).

All the main pathways, when combined with other intermediate channels, have the potential to significantly impact child health investment and the utilization of maternal and child health services by mothers. This could enhance the nutritional outcomes of children.

Figure 1: Conceptual Framework



Notes: The figure presents potential causal pathways through which Bihar Cycle Program impact the nutrition outcomes of children of the mothers exposed to the program.

Source: Altindag et al. (2011); Aslam & Kingdon (2012); Becker & Lewis (1973); Glewwe Paul (1999); Grossman (2008), and authors' intuition.

3. Data

3.1. Data overview

We use the individual-level data from the National Family Health Survey (NFHS-4) conducted in 2015-16. It is a nationally representative cross-sectional survey and a part of the Demographic and Health Surveys (DHS) program. It collects detailed information about married women of reproductive age (15 to 49 years), their health behavior, fertility histories, family planning, and reproductive health, along with their demographic and socioeconomic characteristics. The NFHS also provides information on child anthropometry indicators such as height and weight of children under 5 years of age. Importantly, enumerators measure children's height and weight using appropriate measuring instruments rather than relying on respondents' self-reports, giving us more objective nutrition measurements free from reporting bias. Since the fourth wave of NFHS took place nearly ten years after the program began, the girls exposed to it might have married and given birth by the time of the survey, which makes the timing appropriate for our analysis.

As the study focuses on the impact of the program on child nutrition, we use the retrospective birth history of women, which provides weight and height measurement for children, information on mothers' years of education, and other related variables. We restrict our sample to children aged 0-5 years, born to mothers who were born between 1980 and 1996. We also restrict our sample to birth orders of less than eight to minimize the outlier effect. Thus, our final sample includes 76105 children born to 48532 mothers in the last five years in the states of Bihar, Jharkhand, and Uttar Pradesh.

Our key outcome variables are stunting and underweight. These anthropometric measures of nutrition are based on the height-for-age z-score (HAZ) and weight-for-age z-score (WAZ) of children[6], which were calculated using the WHO's child growth standards. We code stunting (underweight) as a dichotomous dummy variable, assigning a value of 1 if the child's height-

[6] Height-for-age is a measure of linear growth retardation and cumulative growth deficits. Weight-for-age is a composite index of height-for-age and weight-for-height, which accounted for both acute and chronic undernutrition. These direct anthropometric measures are collected by trained enumerators using appropriate measuring instruments rather than relying on self-reports of the respondents.

for-age z-score (weight-for-age z-score) is below minus 2 standard deviations (-2SD) from the median of the WHO reference population. To test the impact of the program on maternal education, we construct two measures of maternal schooling: the total number of years of education by the mother and a dichotomous dummy variable that takes the value 1 if the mother has ever attended secondary school and 0 if they have dropped out after primary schooling[7]. We measure the variable of access to information by constructing dichotomous dummy variables for exposure to mass media sources, separately for newspapers and radio. We construct the internet variable by combining a woman's household's internet and mobile phone access. Due to a lack of data on income and spending at the individual or household level, we used a dichotomous dummy variable of mothers belonging below the poverty line to represent the economic status of the household. Women's age at marriage is calculated as difference between their year of birth and year of marriage and marriage age below 10 is coded as missing to account for outliers and data inconsistencies. We use number of children to capture changes in their reproductive choices. We have constructed the continuum of maternal healthcare utilization variable as a dichotomous dummy assigning value 1 if woman uptakes prenatal, natal, and postnatal services in continuum.

3.2. Identification Strategy

We employ a difference-in-difference technique to estimate intent-to-treat effect. We follow the methodology of Duflo (2001) by utilizing the year of birth and region to determine their exposure to the treatment. In India, the typical age at which students enter grade 9 is 14 to 15. Thus, the girls born in 1990 or earlier who reached the age of 16 or older in 2006 will not benefit from the program, but girls aged 15 or younger in 2006 were exposed to the program, contingent upon their enrollment in senior secondary school. Following nine years of the program, the first cohort of beneficiaries in 2015 was aged 23-24, and the younger girls have had access to it over the last nine years of its continuous operation. The girls who missed out on the program were 25 years or older in 2015.

As we have restricted our sample to mothers born between 1980 and 1996, we can define the treated cohort as the children born to mothers born after 1990. The children of mothers born between 1980 and 1990 form the control group. Thus, we get the first difference by comparing the treated age cohort with the control age cohort, and secondly, we compare it to the same difference in the control states. For the baseline specification, following Mitra & Moene (2017),

[7] As the aim of the cycle program was decrease in drop out of girls after primary schooling and motivate them to continue secondary education with reduced cost of travelling to school.

we use Jharkhand and Uttar Pradesh as the control states for Bihar, as they have geographical and socio-cultural proximity to the state, and there was no such Cycle program for girls during the years around 2006 in these states.

To make the treatment and control groups easier to understand in our study context, we define the exposed (non-exposed) group as those mothers in Bihar who are exposed (not exposed) to the cycle program. The exposed (non-exposed) counterfactual group comprises mothers in the control states of Jharkhand and Uttar Pradesh who are the same age as the exposed (not exposed) group in Bihar.

However, Jharkhand introduced a similar cycle program later in 2010, but it won't affect our analysis as we have restricted our treated cohorts to mothers born only till year 1996[8]. To confirm that our estimates are not confounded by bicycle program in Jharkhand, we show in section 4.3 that our results are robust to narrower age cohorts as the treated group or only Uttar Pradesh as the control state.

The difference-in-difference estimate of the program is given by the following equation:

$$Y_{ibtds} = \beta_0 + \beta_1(Treated_{it} \times Bihar_i) + \beta_2 X_{ibtds} + \theta_b + \mu_t + \delta_{ds} + e_{ibtds} \quad (1)$$

Here, Y_{ibtds} is the outcome of child i born in year b, to mother born in year t, residing in district d in state s,. $Treated_{it}$ takes a value 1 for the child of mothers born in 1991 and later, and 0 for child born to the mothers who were born in 1990 and earlier. $Bihar_i$ is a dummy that takes value 1 for child born in Bihar, and 0 for the child born in Jharkhand or Uttar Pradesh. X_{ibtds} is the vector of control variables that include the mother's region of residence, caste, religion, wealth index, household size, and gender of the head of the household. This set of controls increases the precision of our estimates, as the nutritional outcomes of children could vary due to these individual and household level characteristics. The coefficient θ_b denotes the child's birth-year fixed effect, and μ_t denotes the mother's birth-year fixed effect to control the differential time trends. δ_{ds} is district fixed effect to account for all the time invariant characteristics across the districts, and e_{isbt} denotes the random error term, clustered at the primary sample unit (PSU) level. Since we have included mother's year of birth i.e., μ_t , and

[8] Jharkhand government started free bicycle program in 2010 for girls enrolled in class 8. The age at which girls enter class 8 is 12 to 13, the first set of beneficiaries will be mother born in year 1997 or 1998.

district fixed effect i.e., δ_{ds} , into the specification, they absorb standalone $Bihar$ and $Treated$ dummy respectively. β_1 is the coefficient of interest that measures the change in outcome variables for treatment group in comparison to the control group.

Next, we attempt to investigate some direct and indirect potential channels (mechanisms) through which the cycle program may affect the nutritional outcomes of children. These include mothers who completed years of schooling, completed or did not complete the secondary level of education, income status, age at marriage, number of total births, birth-interval, exposure to media sources, and utilization of maternal healthcare services. We estimate the specification in equation 2 for women i, born in year t, residing in district d in state s.

$$Y_{itds} = \beta_0 + \beta_1(Treated_{it} \times Bihar_i) + \beta_2 X_{itds} + \mu_t + \delta_{ds} + e_{itds} \qquad (2)$$

Here the variable $Treated_{it}$ takes a value 1 for the women born in 1991 and later, and 0 for child born to the mothers born in 1990 and earlier. $Bihar_i$ is a dummy that takes value 1 for child born in Bihar, and 0 for the child born in Jharkhand and Uttar Pradesh. X_{itds} is the vector of control variables, μ_t denotes the mother's year of birth fixed effect, δ_{ds} is district fixed effect and e_{itds} denotes the random error term, clustered at the primary sample unit (PSU) level.

The underlying assumption in the difference-in-difference method is parallel trends, which means that the pre-trends between the treated and control groups should be parallel before the program came into effect. To validate the parallel trend assumption, we conduct an event study as specified in equation 3:

$$Y_{ibtds} = \beta_0 + \sum_{t=t_0}^{t=T} \beta_t 1_t \times Treated_{it} + \beta_2 X_{ibtds} + \theta_b + \mu_t + \delta_{ds} + e_{ibtds} \qquad (3)$$

Here 1_t is an indicator variable that takes value from t_0 to T. t_0 signifies the mothers born in 1980 and T denotes mothers born in the final year of our analysis i.e., 1996. We use $t = 1989 - 1990$ as the base year and estimate the difference in nutrition outcomes of children between treated and control mothers in two-year bands. The coefficient of interest β_t is estimated by interacting each of the time dummy with the treatment dummy. All the other variables are the same as in equation 1. If the estimated β_t is statistically equal to zero in the pre-treatment period, it provides evidence that the treated and non-treated women were trending similarly in the absence of the program.

4. Results

4.1. Descriptive statistics

Table 1 presents the summary statistics of the major socioeconomic, outcome and mechanism variables, separately for the exposed and non-exposed group in Bihar and their corresponding counterfactual groups in the control states of Jharkhand and Uttar Pradesh. As shown in Table 1, in Bihar, the exposed mothers entering for secondary level of education is almost 10 percentage points higher than that of non-exposed mothers; this difference in the control states is only 5 percentage points. The percentage of exposure to newspapers is 26% (20%) among the exposed (non-exposed) mothers in Bihar as compared to 28% (26%) among the corresponding counterfactuals groups in control states. The average number of children born to a treated mother in the treatment state (control states) is 1.63 (1.61) whereas the corresponding figure for the non-exposed mother is 3.09 (2.94). The utilization of continuum of maternal healthcare services is higher among exposed mothers as compared to non-exposed mothers by 6% in Bihar, and 4% in Jharkhand and Uttar Pradesh. The exposed mothers belonging to the lowest wealth quintile in the treatment state (control states) is 49% (35%) whereas the non-exposed mothers belonging to this wealth quintile is 54% (34%).

The average height-for-age z-scores for children of the exposed mothers and non-exposed mothers in Bihar are -1.66 and -1.89 standard deviations, respectively, while the corresponding figures for children of the exposed and non-exposed counterfactual mothers in the control states are -1.63 and -1.73 standard deviations, giving us a preliminary indication that there is an improvement in the height-for-age z-scores of the children whose mothers were exposed to the program. Analogous trends were also observed in the weight-for-age z-scores. In the treatment state of Bihar, the prevalence of stunted children of the exposed mothers is nearly 6 percentage points lower than those of non-exposed mothers; in the control states, this difference is only 4 percentage points. Similarly, the prevalence of underweight children of exposed mothers is percentage points lower than those of non-exposed mothers in Bihar, whereas there is no such difference in the control states.

Table 1: Descriptive statistics of the women and their children sample

Variables	Bihar		Jharkhand & Uttar Pradesh		Combined sample	
	Exposed *Mean (SD)*	**Non-exposed** *Mean (SD)*	**Exposed counterfactual** *Mean (SD)*	**Non-exposed counterfactual** *Mean (SD)*	**Exposed** *Mean (SD)*	**Non-exposed** *Mean (SD)*
Panel A: Mother characteristics						
Age	21.6 (1.57)	28.2 (3.05)	24.2 (1.63)	28.83 (3.01)	22.18 (1.65)	28.66 (3.03)
Birth year	1993 (1.52)	1986 (3.01)	1992 (1.53)	1986 (2.95)	1992 (1.55)	1986 (2.97)
Age at marriage	17.01(2.27)	17.9 (3.39)	18.02 (2.33)	18.9 (3.61)	17.1 (2.67)	17.9 (3.83)
Children ever born	1.63 (0.77)	3.09 (1.35)	1.61 (0.76)	2.94 (1.40)	1.62 (0.77)	2.98 (1.39)
Household size	6.75 (3.26)	6.82 (3.16)	6.90 (3.31)	7 (3.24)	6.86 (3.30)	6.94 (3.22)
Access to Water facility	0.97 (0.14)	0.97 (0.14)	0.90 (0.28)	0.93 (0.24)	0.92 (0.25)	0.95 (0.21)
Access to Toilet facility	0.30 (0.46)	0.29 (0.45)	0.38 (0.48)	0.41 (0.49)	0.36 (0.48)	0.37 (0.48)
Years of education	5.23 (5.04)	3.45 (4.75)	6.88 (4.97)	5.37 (5.60)	6.39 (5.05)	4.77 (5.42)
Secondary education	0.78 (0.41)	0.70 (0.45)	0.80 (0.39)	0.75 (0.43)	0.80 (0.39)	0.74 (0.43)
Read newspapers	0.26 (0.44)	0.20 (0.40)	0.28 (0.45)	0.26 (0.44)	0.28 (0.45)	0.24 (0.42)
Listen to radio	0.18 (0.38)	0.16 (0.37)	0.09 (0.29)	0.10 (0.31)	0.12 (0.32)	0.12 (0.33)
ANC	0.64 (0.47)	0.57 (0.49)	0.82 (0.38)	0.76 (0.42)	0.76 (0.42)	0.70 (0.45)
ANC & ID	0.52 (0.49)	0.43 (0.49)	0.64 (0.47)	0.57 (0.49)	0.60 (0.48)	0.53 (0.49)
ANC, ID & PNC	0.37 (0.48)	0.31 (0.46)	0.49 (0.50)	0.45 (0.49)	0.45 (0.49)	0.41 (0.49)
Female household head	0.22 (0.41)	0.24 (0.43)	0.10 (0.31)	0.11 (0.32)	0.14 (0.35)	0.15 (0.36)
Rural	0.89 (0.30)	0.88 (0.31)	0.79 (0.40)	0.76 (0.42)	0.82 (0.38)	0.80 (0.39)
Caste						
Schedule caste	0.22 (0.41)	0.21 (0.41)	0.19 (0.39)	0.22 (0.41)	0.21 (0.41)	0.21 (0.41)
Schedule tribe	0.03 (0.17)	0.03 (0.17)	0.15 (0.36)	0.07 (0.26)	0.07 (0.26)	0.06 (0.23)
OBC	0.60 (0.48)	0.60 (0.49)	0.51 (0.49)	0.53 (0.49)	0.56 (0.49)	0.55 (0.49)
Others	0.13 (0.34)	0.14 (0.35)	0.13 (0.33)	0.17 (0.38)	0.14 (0.34)	0.16 (0.37)
Religion						
Hindu	0.85(0.35)	0.84 (0.36)	0.75 (0.42)	0.76 (0.42)	0.80 (0.39)	0.79 (0.40)
Muslim	0.14(0.35)	0.15 (0.36)	0.16 (0.37)	0.19 (0.39)	0.16 (0.37)	0.18 (0.38)
Christian	0.0 (0.024)	0.0 (0.01)	0.02 (0.14)	0.01 (0.102)	0.007 (0.08)	0.07 (0.08)
Sikh	0.001(0.02)	0.001 (0.02)	0.001(0.04)	0.001 (0.03)	0.002 (0.04)	0.001 (0.03)
Others	0.0 (0.02)	0.0 (0.01)	0.05 (0.21)	0.021 (0.14)	0.021 (0.14)	0.015 (0.12)
Wealth Quintile						
Poorest	0.49 (0.50)	0.54 (0.49)	0.35 (0.47)	0.34 (0.47)	0.36 (0.47)	0.40 (0.49)
Poorer	0.26 (0.44)	0.23 (0.42)	0.23 (0.42)	0.22 (0.41)	0.26 (0.43)	0.24 (0.39)
Middle	0.13 (0.34)	0.12 (0.32)	0.17 (0.37)	0.16 (0.37)	0.18 (0.38)	0.15 (0.35)
Richer	0.07 (0.26)	0.07 (0.26)	0.13 (0.34)	0.13 (0.34)	0.12 (0.33)	0.11 (0.32)
Richest	0.01 (0.12)	0.02 (0.16)	0.10 (0.30)	0.13 (0.34)	0.07 (0.26)	0.10 (0.30)
Observations	**5050**	**9901**	**11971**	**21610**	**17021**	**31511**
Panel B: Child characteristics						
Child's birthyear	2012 (1.51)	2011 (1.64)	2013 (1.59)	2012 (1.73)	2013 (1.61)	2012 (1.72)
Female child	0.48 (0.49)	0.48 (0.49)	0.48 (0.50)	0.48 (0.49)	0.48 (0.49)	0.48 (0.49)
Anthropometric measures						
HAZ	-1.66 (1.71)	-1.89 (1.67)	-1.63 (1.60)	-1.73 (1.59)	-1.64 (1.63)	-1.81 (1.62)
WAZ	-1.75 (1.15)	-1.83 (1.18)	-1.72 (1.18)	-1.79 (1.14)	-1.73 (1.14)	-1.77 (1.15)
Stunted	0.43 (0.49)	0.49 (0.49)	0.42 (0.49)	0.46 (0.49)	0.42 (0.49)	0.47 (0.49)
Underweight	0.41 (0.49)	0.45 (0.49)	0.40 (0.49)	0.40 (0.49)	0.40 (0.49)	0.42 (0.49)
Observations	**7328**	**17251**	**16972**	**34554**	**24300**	**51805**

Notes: The table reports the summary statistics for the women born between 1980 and 1996 and their children born in the last five years from the date of the survey in the treatment state of Bihar and the control states of Jharkhand and Uttar Pradesh. The exposed (non-exposed) group is the mothers who are exposed (not exposed) to the cycle program in the treatment state of Bihar, whereas the exposed (non-exposed) counterfactual group is the mothers in the control states of Jharkhand and Uttar Pradesh who belong to the same age group as the exposed (not exposed) group in the treatment state. The variables ANC, ID, and PNC denote ante-natal care, institutional delivery, and post-natal care, respectively. Standard deviations are reported in parenthesis.

Source: Author's calculations from NFHS-4

4.2. Main Results

Table 2 presents the results of the effects of the cycle program on child nutrition indicators. We first look at the effect on stunting, which is a long-term nutritional deprivation in children. We use the basic model of equation 1 to find the coefficient in Columns 1 and 2, considering the fixed effects of the mother's and child's birth year and the district. The coefficient is negative and statistically significant. It can be interpreted as the children of treated mothers are 4.6 percentage points ($p<0.01$) less likely to be stunted as compared to the children of mothers in the control group. In Column 2, when we include controls for potential confounders such as the mother's region of residence, religion, social category, household size, wealth status, and sex of head of household, among others, the magnitude of the coefficient of interest drops to 4.1 percentage points ($p<0.01$).

Table 2: Bihar cycle program and child nutrition outcomes

	(1)	(2)	(3)	(4)
	Stunting		**Underweight**	
Treated*Bihar	-0.046***	-0.041***	-0.027***	-0.023**
	(0.010)	(0.009)	(0.010)	(0.010)
Child-birth year FE	Yes	Yes	Yes	Yes
Mother birth year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	62,846	62,494	62,846	62,494
R-squared	0.047	0.085	0.028	0.060

Notes: The sample consists of children aged 0 to 5 years. Treated is assigned a value of 1 for women born post-1990, and 0 otherwise. Bihar is assigned a value of 1 if the mother originates from Bihar and a value of 0 if she is from Jharkhand or Uttar Pradesh. Stunting is a dummy variable that assumes the value of 1 if the height-for-age z-score is below -2 and zero otherwise. Underweight takes a value of 1 if the weight-for-age z-score is less than -2 and zero otherwise. Controls include the birth order of the child, the region of residence, caste, religion, wealth index, household size, and sex of the household head. Regression additionally accounts for child's birth year, mother's birth year and district fixed effects. We cluster the standard errors at the PSU level and report them in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

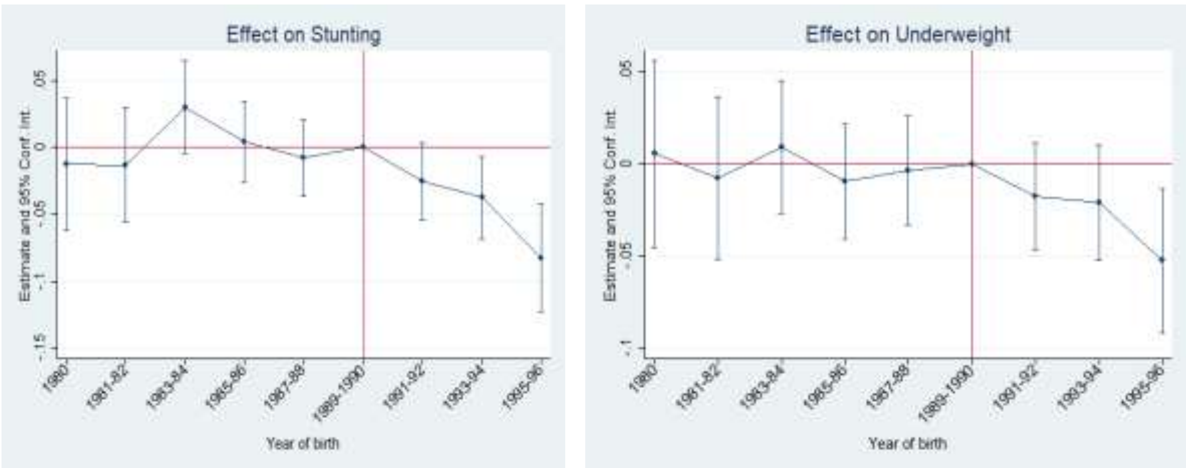
Source: Author's calculations from NFHS-4

Next, in Column 3, we show the results for underweight, and we find that the program decreases the probability of being underweight for children of younger mothers in Bihar by 2.7 percentage points (p<0.01). In Column 4, when we include controls for the socioeconomic and household characteristics, the coefficient of interest remains stable and statistically significant (p<0.05). Overall, the results indicate that children of mothers potentially exposed to the cycle program are 2.3 percentage points (p<0.05) less likely to be undernourished when compared to children of unexposed mothers.

4.3. Identifying Assumption

Figure 2 reports the estimates of equation 3, and our results validate the parallel trend assumption. The graph shows that the estimated difference in the outcome for children of the mothers born before 1990 in the treated and control state is small and statistically insignificant. Also, the nutritional outcomes for the children of mothers born after 1990 and exposed to the program are statistically significant and different from zero.

Figure 2: Parallel trend test



Notes: This figure shows the event study plots of the impact of Bihar cycle program on child nutrition outcomes to validate the parallel trends assumption. Stunting is a dummy variable that assumes the value of 1 if the height-for-age z-score is below -2 and zero otherwise. Underweight takes a value of 1 if the weight-for-age z-score is less than -2 and zero otherwise. On the x-axis, we have the mother's year of birth, and the base year is 1989-1990. Each dot represents the coefficient for the indicated mother's year of birth. The error bars report a 95% confidence interval for each coefficient estimated using robust standard errors. The regression controls for the birth order of the child, the region of residence, caste, religion, wealth index, household size, and sex of the household head, and includes child's birth year, mother's birth year and district fixed effects.

Source: Author's calculations from NFHS-4

4.4. Mechanism Analysis

In this section, we present the estimates of equation 2 on the various channels driving our main results. We begin by reporting the effects on mothers' education and economic status. Columns 1 and 2 of Table 3 indicate that the program's effect is positive and significant on mother's education. We can infer that the treated group of women completed 0.152 more years of education ($p<0.1$) than the control group of women. They are more likely to attain secondary or higher levels of education by 3.1 percentage points ($p<0.01$).

Table 3: Bihar cycle program and women education outcomes (Mechanism)

	(1)	(2)	(3)	(4)	(5)
	Years of Education	**Secondary Education**	**Newspaper**	**Radio**	**Internet**
Treated*Bihar	0.152*	0.031***	0.037***	0.018**	0.008*
	(0.088)	(0.011)	(0.008)	(0.007)	(0.004)
Mother birth year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	48,241	28,268	48,241	48,241	48,241
R-squared	0.421	0.159	0.252	0.071	0.192

Notes: The sample comprises all women aged 18 to 35 who have given birth in the last five years. Treated takes value 1 for women born after 1990, and 0 otherwise. Bihar takes value 1 if the mother is from Bihar and 0 if they are from Jharkhand or Uttar Pradesh. Years of education indicates the completed years of education by the women, and secondary is a dummy for women who have entered the secondary level of education. The variable newspaper is a dummy that takes the value 1 if women frequently read newspapers and 0 otherwise, and the variable radio takes the value 1 if women regularly listen to the radio and 0 otherwise. The internet is a dichotomous dummy that takes the value 1 if the women live in a household having access to the internet. Controls include the mother's region of residence, caste, religion, wealth index, household size, and the sex of the household head. Regression also controls the mother's birth year and district fixed effects. We cluster the standard errors at the PSU level and report them in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations from NFHS-4

Next, we see the program's effect on exposure to media sources, i.e., newspapers, radio, and the internet. Columns 3 to 5 of Table 3 present the estimates. The results uphold our hypothesis that an educated woman is more likely to access information through newspapers, television, or radio and translate that knowledge to provide a healthier lifestyle to their children (Le & Nguyen, 2020). The program increased the frequency of reading newspapers and listening to radio by 3.7 ($p<0.01$) and 1.8 ($p<0.1$) percentage points, respectively, for the exposed women in Bihar. The probability of accessing the internet in the household via mobile phone also increased by 0.8 ($p<0.1$) percentage points for the treated women, consistent with the observation that internet usage for acquiring health knowledge is greater among educated women (Pandey et al., 2003).

We further investigate the effect on women's economic status, presenting the results in Table 4. We measure their standard of living by their poverty status, and access to basic sanitation facilities. Access to clean drinking water and in-home toilets can improve child nutrition through the prevention of diseases and reduction in open defecation (Singh et al., 2021). The estimate in Column 1 indicates that the exposed mothers are 3.1 percentage points ($p<0.01$) less likely to belong to a household below the poverty-line. They are 0.6 and 3.3 ($p<0.01$) percentage points more likely to have access to clean water and toilet facility respectively.

Next, in Table 4, we show the program's effect on mothers' ages at marriage and fertility behavior, as delay in marriage results in improvement in child well-being (Chari et al., 2017). The results are in line with the literature suggesting the education level of women's association with delay in marriage and reduction in the number of births of women (Currie & Moretti, 2011; Grepin & Bharadwaj, 2015; Keats, 2018; Samarakoon & Parinduri, 2015; Zhang & Assaad, 2024). Column 4 shows that age at marriage increases by 0.044 years for the treated group, however, it is not statistically significant. The estimates in Columns 5 and 6 of Table 4 show that for the younger cohorts residing in Bihar, the interval between consecutive births increases by 2.8 ($p<0.01$) months years, and they have 0.08 ($p<0.01$) fewer births in comparison to the older cohorts in Bihar.

Table 4. Mechanism Analysis: Bihar cycle program on women's economic status, fertility outcomes and healthcare utilization

	Economic status			Fertility outcomes			Healthcare utilization		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Belong to BPL	**Water facility**	**Toilet facility**	**Age at marriage**	**Fertility**	**Birth interval**	**ANC**	**ANC & ID**	**ANC& ID & PNC**
Treated*Bihar	-0.031***	0.006	0.033***	0.044	-0.084***	2.80***	0.023**	0.021**	0.016
	(0.010)	(0.004)	(0.007)	(0.056)	(0.020)	(0.373)	(0.009)	(0.010)	(0.010)
Mother birth year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,188	48,241	48,241	47,438	48,241	35,049	48,139	48,162	48,191
R-squared	0.183	0.194	0.552	0.193	0.463	0.142	0.173	0.157	0.138

Notes: The sample consists of women aged 18-35 years who have given birth in the last five years. Treated takes a value of 1 for women born post-1990, and 0 otherwise. Bihar takes value 1 if the mother is from Bihar and 0 if they are from Jharkhand or Uttar Pradesh. The variable 'belong to BPL' is a dichotomous dummy that takes the value 1 for mothers living in households below the poverty line. The dummy variables 'water facility' and 'toilet facility' take value 1 if the household has access to clean drinking water and toilet facilities, respectively. The variable age at marriage indicates the age when women first got married, and variable fertility defines the total number of births of women. Birth interval defines the gap between retrospective births of women. The continuum of MCH services includes integrated service delivery for mothers and children, from pre-pregnancy to delivery, and an immediate postnatal period. The variables ANC, ID, and PNC denote ante-natal care, institutional delivery, and post-natal care, respectively. ANC is a dummy that takes the value 1 if women went for at least one antenatal checkup and 0 otherwise. ANC & ID is a dummy for women if they have gone for ANC and delivered in a health facility. ANC & ID & PNC is a dummy for women going for post-natal checkup safter institutional delivery and prenatal care (that is, continuum of care). Controls include mother's region of residence, caste, religion, wealth index, household size, and sex of household head. Regression also controls the mother's birth year and district fixed effects. Standard errors are clustered at the PSU level and reported in parentheses.

Further, in Table 4, we present the results regarding the healthcare-seeking behavior of mothers (Column 7-9). The literature suggests that education would lead to an increase in maternal and child health care utilization. The result in Column 7 suggests that an exposed mother is 2.3 percentage points ($p<0.05$) more likely to go for antenatal checkups during her pregnancy. In Columns 8 and 9, we estimate the program's effect on the uptake of the 'continuum' in maternal care services. The estimates have positive and statistically significant coefficients. This means that mothers exposed to the program are 2.1 percentage points ($p<0.05$) more likely to get prenatal care and opt for institutional delivery (facility-based childbirth), and 1.7 percentage points more likely to get antenatal care, opt for institutional delivery, and get post-natal care in a 'continuum' than the unexposed mothers.

4.5. Heterogeneity Analysis

We explore the heterogeneity in effects across several subsamples categorized by the sex of the child, i.e., boy or girl; living standard, i.e., poor or non-poor; and caste, i.e., low caste or high caste. Table 5 (panel A) presents the findings regarding the stunting of the children of exposed mothers. We can infer from Columns 1 and 2 that the exposure to the cycle program led to a decline in stunting by 4.8 percentage points ($p<0.01$) for boy children and 3.5 percentage points ($p<0.01$) for girl children. A child of an exposed mother belonging to poor households is less likely to be stunted by 3.3 percentage points ($p<0.01$) in comparison to a decline of 4.3 percentage points ($p<0.05$) in non-poor households (Columns 3 and 4). The estimates in Columns 5 and 6 show that the benefited children from low-caste households are 4.1 percentage points ($p<0.01$) less likely to be stunted, while the improvement in high-caste household's children is 4.9 percentage points ($p<0.1$).

Table 5 (panel B) presents the findings regarding the underweight of children for the sample segregated by wealth, caste and sex of child. Like stunting, we find that the decline in the probability of being underweight is larger for boys than for girls, with a decline of 2.5 percentage points ($p<0.1$) for boy children, and 2.1 percentage points for girl children (Columns 1 and 2). We can infer from Column 3 and 4 that the effects of the program on the decline in underweight children are larger for the non-poor counterparts as compared to poor but insignificant. Lastly, Columns 5 and 6 indicate that unlike the result for stunting, children of mothers belonging to low castes benefit more compared those from high castes, and they are 2.3 percentage points ($p<0.05$) less likely to be underweight.

Table 5: Bihar cycle program and child nutrition outcomes on different subsamples

	(1)	(2)	(3)	(4)	(5)	(6)
	Boy	**Girl**	**Poor**	**Non-poor**	**Low caste**	**High caste**
	Panel A: Stunting					
Treated*Bihar	-0.048***	-0.035***	-0.033***	-0.043**	-0.041***	-0.049**
	(0.013)	(0.013)	(0.012)	(0.017)	(0.010)	(0.025)
Observations	32,522	29,972	39,953	22,541	52,919	9,575
R-squared	0.081	0.098	0.061	0.054	0.076	0.100
	Panel B: Underweight					
Treated*Bihar	-0.025*	-0.021	-0.018	-0.028	-0.023**	-0.022
	(0.013)	(0.013)	(0.012)	(0.018)	(0.010)	(0.025)
Child-birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mother birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,522	29,972	39,953	22,541	52,919	9,575
R-squared	0.061	0.067	0.035	0.038	0.051	0.075

Notes: The sample comprises children 0-5 years of age born to women aged 18-35 years. Treated takes value 1 for women born after 1990, married after 2006, and 0 otherwise. Bihar takes value 1 if the mother originates from Bihar and 0 if she is from Jharkhand or Uttar Pradesh. Stunting is a dummy variable that takes the value 1 if the height-for-age z-score is below -2 and 0 otherwise. Underweight takes the value 1 if the weight-for-age z-score is less than -2, and 0 otherwise. Poor is defined as women belonging bottom two wealth quintile. Low caste defines women belonging to scheduled tribes, scheduled castes, and other backward castes. Controls include birth order of the child, region of residence, caste, religion, wealth index, household size, and sex of household head. Regression also controls the child's birth year, mother's birth year and district fixed effects. Standard errors are clustered at the PSU level and reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Source: Author’s calculations from NFHS-4

4.6. Robustness Checks

To strengthen the validity of our results, we conduct a series of robustness tests. We further present the effect on height-for-age z-score (HAZ) and weight-for-age z-score (WAZ). Column 1 (Table A1) shows that HAZ increases by 0.136 ($p<0.01$) standard deviations for the children of mothers exposed to the program. In Column 2, with control variables included in the model, the increase in HAZ decreases marginally to 0.12 ($p<0.01$) standard deviations. Column 3 indicates that WAZ will rise by 0.053 ($p<0.05$) standard deviations for children of treated mothers to those of untreated mothers. With controls, the augmentation in WAZ is 0.041 ($p<0.1$) standard deviations.

Next, to confirm that our results are not confounded by a similar bicycle program introduced by Jharkhand in 2010, we estimate the specification in equation 1 with a different control state and narrower age cohorts. First, we use only Uttar Pradesh exclusively as the control state for Bihar. Table A2 displays the estimated results. The results are generally aligned with our main results, and the coefficients are somewhat elevated when the state of Jharkhand is excluded. Children born to treated women in Bihar exhibit a 4.3 percentage point ($p<0.01$) reduction in the likelihood of stunting and a 2.7 percentage point ($p<0.01$) reduction in the likelihood of being underweight, in comparison to children born to women in Uttar Pradesh.

Secondly, using narrower age cohorts we estimate equation 1 and present the results in Table A3. Here, we define women to be treated 1 if mothers were born between 1991 and 1993 and unmarried until 2006; thus, the treated cohort is aged between 13 and 15 years in 2006 (as opposed to 10 to 15 years). The control group comprises women born between 1988 and 1990, thus aged 16 to 18 years in 2006 (as opposed to 16 to 26 years). Similarly, treated 2 is defined as excluding mothers born on margin years. It takes a value of 1 if the mother was born from 1992 to 1995, and 0 if she was born between 1984 and 1989. Columns 1 to 4 in Table A3 depict that the results align with the main results and do not change much.

Third, to confirm that our results are not spurious and fulfill our identification assumption, we follow Duflo (2001) and conduct a falsification test by restricting our sample to children of mothers born before 1991. With the restricted sample, we construct two placebo treatment variables by taking two random years in pre-intervention data and check if the coefficient of interest in equation 1 varies in the pre-intervention period in Bihar. The variable Pseudo-1 is a dummy that takes the value 1 for the children born to mothers born after 1985, and Pseudo-2 defines children of mothers born after 1987 as the treated cohort. The results are presented in Table A4, and Columns 1 to 4 show that the estimated coefficients are close to zero and statistically insignificant for all the outcome variables. It suggests that the pseudo-treated group of cohorts in Bihar did not have a significantly different effect on the outcome variables as compared to the reference group in the control state.

Next, we test for exact randomization where we randomly assign states to be treated or non-treated. We re-estimated equation 1, 1000 times for each placebo treatment and the results in Figure A1 show that the simulated estimates are centered around zero and much lower than our actual estimates. Additionally, to confirm that our results are not biased due to differences in observed covariates across treatment and control states, we use kernel propensity scores to match treatment and control groups using individual and household level characteristics. We re-estimate equation 1 on the matched sample and use weights corresponding to the kernel propensity scores. The results in Table A5 are consistent with our main results. These findings together provide confidence in the validity of our results.

Lastly, to test that the heterogeneous treatment effects are not biasing our results, we present robust estimates based on the diagnostics proposed by Sloczynski (2022). We re-estimated the Average Treatment Effects (ATE) as a weighted average of ATT and ATU. The results in Table A6 shows that the Average Treatment Effects (ATE) are much larger using this specification, but the $\hat{w}_0$ is 0.019, suggesting that OLS is expected to bias our estimates by only 1.9 % of the difference between the Average Treatment effects on the Untreated (ATU) and Average Treatment effects on the Treated (ATT) (both of which are negative and statistically significant at the $p<0.01$ level). Thus, OLS is an appropriate choice of model. Given the larger $\hat{\delta}$, our estimates are better interpreted as an ATT more than an ATE.

4.7. Addressing confounding policies

In this section, we examine whether the estimated impact of the Bihar Cycle Program on child nutrition could be confounded by other contemporaneous policies. One such policy is the Dhanalakshmi Scheme, implemented in 2008, which aimed to improve the child sex ratio and promote girls' education through conditional cash transfers and insurance coverage for girls born after November 2008. While this scheme did not directly affect the mothers in our sample, it could potentially influence the health outcomes of girl children. To mitigate this concern, we restrict our analysis to male children who were not eligible for the Dhanalakshmi Scheme. The results, reported in Table 5 (column 1), remain statistically significant, suggesting that the observed effects are not driven by this policy. Additionally, since Dhanalakshmi was implemented across seven states, including Bihar, Jharkhand, and Uttar Pradesh, it would not have induced differential post-policy changes between our treatment and control states.

Another relevant policy is the Prohibition of Child Marriage Act (2006), which sought to reduce child marriage and could plausibly have influenced girls' educational attainment by delaying the age at marriage. However, as this policy was enforced nationwide, it would not differentially affect the states in our study and is unlikely to bias our estimates. The Bihar Alcohol Prohibition Policy, introduced in 2016, may have had broader social impacts, including on child health. However, our sample is restricted to children born up to 2016, and thus any potential effects of this policy would not influence our findings. Thus, the estimated effects of the Bihar Cycle Program are unlikely to be confounded by these contemporaneous interventions.

5. Discussion and Conclusion

The paper examines the intergenerational effect of a school cycle program, finding that it positively impacts child nutrition. An increase in mothers' education decreases the probability of children born to exposed mothers being stunted and underweight. The results align with the existing evidence linking maternal schooling to improved child health outcomes (Currie & Moretti, 2003). We identify several mediating channels underlying these effects. First, we find that program exposed cohorts are more likely to complete their secondary education than the unexposed cohorts. In addition, we demonstrate that an increase in girls' years of education translates into girls having fewer children, which ultimately affects child health and nutrition. The mother's education effect on child nutrition also operates through increases in their media exposures, standard of living, and utilization of maternal healthcare services. Future research may further investigate the effect of the program on the educational outcomes of children once the program matures for some more years. Future research, by exploring appropriate data availability, may also estimate the differential effects based on the distance between the girls' village and the nearest secondary school.

The program effects vary across caste, and income as children from upper castes, and non-poor groups benefit more from it than their counterparts. Gender disparities are also evident with boys showing greater improvement in nutrition relative to girls. We conduct several robustness checks to support the credibility of our findings. These include tests for parallel trend assumption, use of alternative control state, narrower age cohorts, and propensity score matching. Our results may have policy implications for other Indian states that are considering implementing school cycle programs to enhance girls' secondary education. Our study findings could be applicable to other low- and middle-income countries as well, suggesting that investing in similar programs aimed at enhancing women's education would reap long-term societal benefits through intergenerational effects.

However, some data and methodological concerns may warrant a cautious interpretation of our results. While our design is based on plausible treatment assignment using birth cohorts, concerns remain about non-compliance, as we cannot fully verify whether all treated girls completed secondary school after receiving the bicycle. Nonetheless, Muralidharan & Prakash (2017) provides strong evidence of increased enrollment and reduced dropout rates due to the program. Another concern is our reliance on typical age of girls entering standard 9 as the cut-off point, which may vary for different individuals. However, to overcome this potential bias, we have used wider age cohorts for the treated and control groups. Lastly, we could not use the latest wave of NFHS for our analysis, as several child-specific nutrition programs started in Bihar as well as in control states after 2016, which could potentially overestimate the program's effect.

The Cycle program was originally aimed at reducing the gender gap in schooling by increasing school enrolment of girls, but it has had several unintended effects on the beneficiaries, including improvements in child nutrition. By analyzing its long-term effect in our study, our findings underscore the broader societal benefits of investing in girls' education, including the potential to reduce intergenerational inequality and malnutrition. Investment in the education level of mothers today can benefit multiple future generations and reduce intergenerational inequality. To achieve both Sustainable Development Goals 2.2 (ending malnutrition) and 4 (equitable quality education), it is important to address both demand- and supply-side problems. Giving people quality resources and removing barriers that limit their effective utilization can achieve this. We suggest that policymakers invest in infrastructure elements to maximize the benefits of such programs. Infrastructure elements, including school construction, all-weather roads, and transportation, need to be adequately resourced to increase girls' educational attainment along with interventions like the cycle program (Seebacher, 2023). Additionally, complimentary interventions can enhance the long-term spillovers and intergenerational benefits of such programs.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement

The data used in the study is secondary data from DHS which is publicly available.

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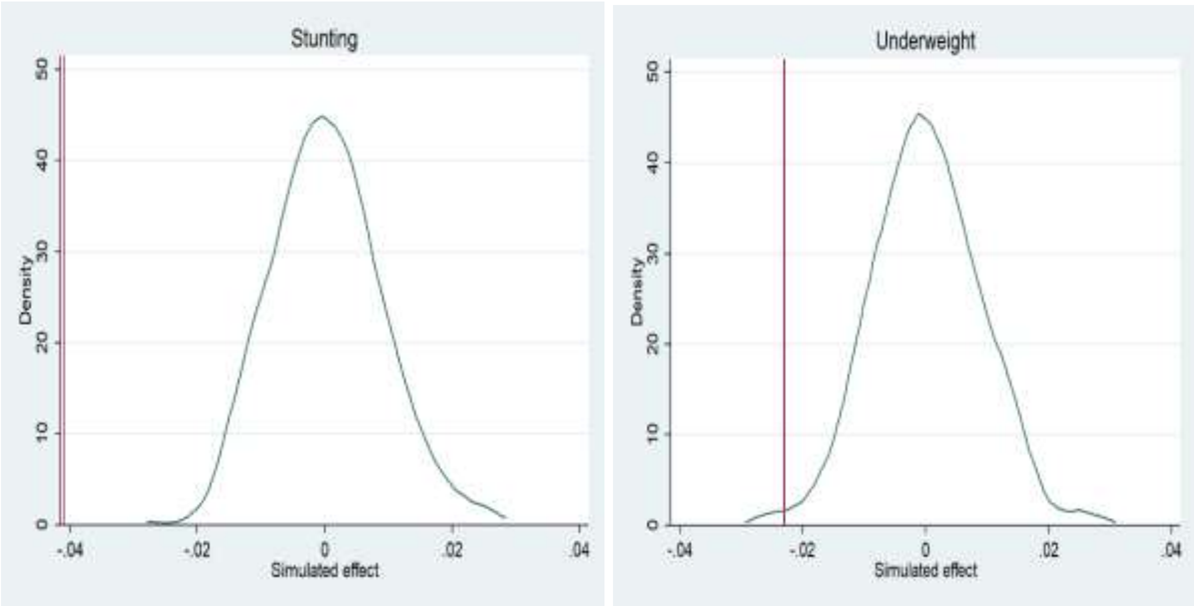
APPENDIX

Figure A1: Exact randomization test



Notes: The graph plots the coefficient from the exact randomization test, where the treatment state was randomly reshuffled 1000 times. The vertical red line indicates the coefficient estimated from the actual treatment state using equation 1. Controls include birth order of the child, region of residence, caste, religion, wealth index, household size, and sex of household head. Regression also controls the child's birth year, mother's birth year and district fixed effects.

Table A1: Bihar cycle program and child nutrition outcomes (Additional results)

	(1)	(2)	(3)	(4)
	HAZ score		**WAZ score**	
Treated*Bihar	0.136***	0.120***	0.053**	0.041*
	(0.033)	(0.032)	(0.024)	(0.023)
Child-birth year FE	Yes	Yes	Yes	Yes
Mother birth year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	62,846	62,494	62,846	62,494
R-squared	0.071	0.112	0.038	0.089

Notes: The sample comprises children 0-5 years of age born to women aged 18-35 years. Treated takes value 1 for women born after 1990, and 0 otherwise. Bihar takes value 1 if the mother is from Bihar and 0 if they are from Jharkhand or Uttar Pradesh. The variable HAZ is height for age z scores, and WAZ is weight for age z scores. Controls include birth order of the child, region of residence, caste, religion, wealth index, household size, and sex of household head. Regression also controls the child's birth year, mother's birth year and district fixed effects. Standard errors are clustered at the PSU level and reported in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: Author's calculations from NFHS-4

Table A2: Robustness test: Change in control state

	(1)	(2)	(3)	(4)
	Stunting		**Underweight**	
Treated*Bihar	-0.044***	-0.043***	-0.027***	-0.027***
	(0.010)	(0.010)	(0.010)	(0.010)
Child-birth year FE	Yes	Yes	Yes	Yes
Mother birth year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	53,206	52,923	53,206	52,923
R-squared	0.051	0.089	0.025	0.057

Notes: The sample comprises children 0-5 years of age born to women aged 18-35 years. Treated takes value 1 for women born after 1990, and 0 otherwise. Bihar takes value 1 if the mother is from Bihar and 0 if they are Uttar Pradesh. Stunting is a dummy variable that takes the value 1 if the height-for-age z-score is below -2 and 0 otherwise. Underweight takes the value 1 if weight-for-age z-score is less than -2, and zero otherwise. Controls include birth order of the child, region of residence, caste, religion, wealth index, household size, and sex of household head. Regression also controls the child's birth year, mother's birth year and district fixed effects. Standard errors are clustered at the PSU level and reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations from NFHS-4

Table A3: Robustness test: Change in age cohorts

	(1)	(2)	(3)	(4)
	Stunting		**Underweight**	
Treated1*Bihar	-0.024*		-0.016	
	(0.012)		(0.013)	
Treated2*Bihar		-0.032***		-0.021*
		(0.012)		(0.012)
Child-birth year FE	Yes	Yes	Yes	Yes
Mother birth year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	32,441	32,542	32,441	32,542
R-squared	0.081	0.086	0.060	0.062

Notes: The sample comprises children 0-5 years of age born to women aged 18-35 years. Treated1 takes value 1 for women born between 1991 and 1993, and 0 for women between 1988 and 1990. Treated2 takes value 1 for women born between 1992 and 1995, and 0 for women between 1985 and 1988. Bihar takes value 1 if the mother is from Bihar and 0 if they are from Jharkhand or Uttar Pradesh. Stunting is a dummy variable that takes the value 1 if the height-for-age z-score is below -2 and 0 otherwise. Underweight takes the value 1 if weight-for-age z-score is less than -2, and zero otherwise. Controls include birth order of the child, region of residence, caste, religion, wealth index, household size, and sex of household head. Regression also controls the child's birth year, mother's birth year and district fixed effects. Standard errors are clustered at the PSU level and reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations from NFHS-4

Table A4: Placebo Test

	(1)	(2)	(3)	(4)
	Stunting		**Underweight**	
Pseudo1*Bihar	-0.011		-0.001	
	(0.011)		(0.012)	
Pseudo2*Bihar		-0.014		0.002
		(0.011)		(0.011)
Child-birth year FE	Yes	Yes	Yes	Yes
Mother birth year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	41,364	41,364	41,364	41,364
R-squared	0.088	0.089	0.062	0.062

Notes: The sample comprises children 0-5 years of age born to women born till 1990. Pseudo1 takes value 1 for women born after 1985, 0 otherwise, and Pseudo2 is a dummy for women born after 1987, 0 otherwise. Bihar takes value 1 if the mother is from Bihar and 0 if they are from Jharkhand or Uttar Pradesh. Stunting is a dummy variable that takes the value 1 if the height-for-age z-score is below -2 and 0 otherwise. Underweight takes the value 1 if weight-for-age z-score is less than -2, and zero otherwise. Controls include birth order of the child, region of residence, caste, religion, wealth index, household size, and sex of household head. Regression also controls the child's birth year, mother's birth year and district fixed effects. Standard errors are clustered at the PSU level and reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations from NFHS-4

Table A5: Bihar cycle program and child nutrition outcomes using PSM

	(1) **Stunting**	(2) **Underweight**
Treated*Bihar	-0.031***	-0.018*
	(0.010)	(0.011)
Child-birth year FE	Yes	Yes
Mother birth year FE	Yes	Yes
District FE	Yes	Yes
Controls	Yes	Yes
Observations	62,493	62,493
R-squared	0.082	0.053

Notes: The sample comprises children 0-5 years of age born to women aged 18-35 years. The table presents difference-in-difference estimates using kernel propensity scores matching. Probit model is used to estimate propensity scores, and covariates used for matching are region of residence, caste, religion, wealth, household size, sex of household head and child's birth order. Treated takes value 1 for women born after 1990, and 0 otherwise. Bihar takes value 1 if the mother is from Bihar and 0 if they are from Jharkhand or Uttar Pradesh. Stunting is a dummy variable that takes the value 1 if the height-for-age z-score is below -2 and 0 otherwise. Underweight takes the value 1 if weight-for-age z-score is less than -2, and zero otherwise. Controls include the birth order of the child, region of residence, caste, religion, wealth index, household size, and sex of household head. Regression also controls the child's birth year, mother's birth year and district fixed effects. Standard errors are clustered at the PSU level and reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations from NFHS-4

Table A6: Bihar cycle program and child nutrition outcomes (heterogeneous treatment effects)

	(1)	(2)	(3)	(4)
	Stunting		**Underweight**	
	Original Estimates			
OLS	-0.046***	-0.041***	-0.027***	-0.023**
	(0.010)	(0.009)	(0.010)	(0.010)
	Decomposition			
$\widehat{ATT}$	-0.017***	-0.052***	0.005	-0.022***
	(0.006)	(0.006)	(0.006)	(0.006)
$\widehat{\omega_1}$	0.980	0.971	0.980	0.971
$\widehat{ATU}$	-0.155***	-0.185***	-0.060***	-0.111***
	(0.018)	(0.018)	(0.016)	(0.018)
$\widehat{\omega}_0$	0.019	0.028	0.019	0.028
$\widehat{ATE}$	-0.141***	-0.171***	-0.054***	- 0.102***
	(0.016)	(0.016)	(0.015)	(0.015)
$\hat{\delta}$	-0.878	-0.870	-0.878	-0.870
Child-birth year FE	Yes	Yes	Yes	Yes
Mother birth year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	62,886	62,494	62,886	62,494

Notes: The sample consists of children aged 0 to 5 years. Stunting is a dummy variable that assumes the value of 1 if the height-for-age z-score is below -2 and zero otherwise. Underweight takes a value of 1 if the weight-for-age z-score is less than -2 and zero otherwise. Controls include the birth order of the child, the region of residence, caste, religion, wealth index, household size, and sex of the household head. Regression additionally accounts for child's birth year, mother's birth year and district fixed effects. Clustered standard errors at the PSU level (OLS) and bootstrapped standard errors ($\widehat{ATT}, \widehat{ATU}\ and\ \widehat{ATE}$) are reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations from NFHS-4