# RETURNS TO EDUCATION, CHILD LABOR & SCHOOLING IN INDIA *

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**Abstract**

In an environment where children's time has an economic value and employment opportunities for educated workers are scarce, parental investments in their children's education may not be driven entirely by poverty and credit constraints. We offer evidence that children's participation in child labor and schooling responds to economic returns to education in India, which suggests implementing policies that raise the economic benefits of education - such as creating more high-skilled jobs and improving the quality of education - in order to lower child labor and increase schooling.

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# I INTRODUCTION

While poverty, credit constraints, and the absence of social welfare systems are cited as the major determinants of children's participation in work and school, these are often not the most critical determinants of child labor and education in developing economies. Low economic returns to basic education are a characteristic of several developing countries, driven not only by a scarcity of employment opportunities for educated workers and the difficulty in securing high-skilled jobs but also by an inferior quality of education in the majority of schools. In many developing countries, high-skilled jobs are often secured not by academic merit and experience but rather by economic status and family connections, making under-privileged parents undermine the value of education. The scarcity and inadequacy of teachers and schools, inferior teaching facilities, and inaccessible schools reinforce many parents' beliefs that education is a worthless endeavor and that their children are better off learning skills at work rather than attending school.

In the literature, the relationship between returns to education, child labor, and schooling has not been sufficiently explored. The bulk of the theoretical literature on child labor focuses on poverty and credit constraints as the main causes of child labor (Basu & Van 1998, Basu 2002, Ranjan 1999). Another strand of the literature examines the impact of trade on child labor (Jafarey & Lahiri 2002, Edmonds & Pavcnik 2004, Cigno et al. 2002). Yet another strand investigates the impact of technological changes on schooling (Foster & Rosenzweig 1996, Dessy & Pallage 2001). Several empirical studies provide evidence that child labor and schooling are affected by more general local economic conditions such as economic growth (Barros et al. 1994, Neri & Thomas 2001, Swaminathan 1998), unemployment (Da Silva Leme & Wajnman 2000), and labor markets (Duryea & Arends-Kuening 2002, Krueger 2002).

In this paper, we empirically examine the relationship between rates of return to schooling, child labor, and education in India using individual-level household data from the Employment and Unemployment Schedule of the National Sample Survey Organization (NSSO). After correcting for selection bias using the method developed by Bourguignon et al. (2001), we first estimate the rates of return to primary, middle, high school, and college education for males and females in each Indian state for four years - 1983, 1988, 1993, and 1999. We then estimate how participation in child labor and schooling responds to rates of return to primary and middle school. Our results indicate that participation in child labor falls for both boys and girls in response to higher rates of return to education. However, schooling only amongst boys increases in response to higher rates of return to education.

The structure of this paper is as follows: Section II provides a brief background on child labor and education in India. Section III describes the data and Section IV outlines the empirical analysis. Section V presents the empirical evidence and Section VI described our robustness checks. Section VII concludes.

## II CHILD LABOR & EDUCATION IN INDIA

### 1. Variation in Child Labor & Education

As Table 1 in the Appendix shows, India is characterized by vast disparities in literacy rates across gender, urban and rural regions, castes, and states. Table 3 in the Appendix illustrates variation amongst India's states and union territories with respect to child labor and schooling. In 1999, 54% of children in Gujarat were engaged in child labor (defined as the proportion of hours children spent in market work, household enterprise work, or domestic activities) while child labor in Himachal Pradesh was only 7%. In 1999, schooling (defined as the proportion of hours children spent attending school) was highest in the state of Kerala at 94% and lowest in Bihar at 51%.

While urban-rural and male-female differences in child labor and schooling are significant in India, these gaps have been diminishing over time. Table 4 in the Appendix shows an urban and male bias towards more schooling and less child labor compared to rural and female children. While schooling has been increasing from 1983 to 1999, our data shows an increase in child labor between 1983 and 1988 followed by a decrease from 1988 until 1999.

## 2. Legislation on Child Labor & Education

Despite the existence of anti-child labor and compulsory education legislation in India, these laws are rarely enforced.[1] Opposition from employers and parents of child laborers creates political pressures that discourage enactment of these laws, which are summarized in Table 2 in the Appendix. The Child Labor Prohibition & Regulation Act (August, 1986) prohibits the employment of children below the age of 14 in certain occupations and processes, while regulating work conditions in other jobs.[2] Because this law only covers factories with more than 10 workers and since most children work in the informal sector and in unregistered factories with less than 10 workers, they are not protected by it. Children working in factories with over 10 workers are usually not

[1] Child laborers, according to the International Labor Organization and the Indian Census, consist of children in the age group 5-14 years who are economically active (i.e. those who earn a wage or whose labor results in output for the market.

[2] Children are prohibited from employment in bidi-making; carpet-weaving; cement manufacturing; cloth printing, dyeing, and weaving; match manufacturing; explosives and fireworks; mica cutting and splitting; shellac manufacturing; soap manufacturing; tanning; wool cleaning; and building and construction work. Children are also prohibited from working on railway and port premises.

recorded in the register. Employers who violate this law are required to pay a small fine, after which they continue to employ children.

With respect to education, article 45 of the Indian Constitution declares that 'the State shall endeavor to provide free and compulsory education for all children until they complete the age of 14 years'.[3] However, given the widespread notion in India that it is not essential for all children to be educated, it is almost impossible for the State to monitor school enrollment and attendance.

## III DATA SOURCE

The individual level data used in this study comes from the Employment and Unemployment Schedule of the National Sample Survey Organization (NSSO), administered nationally by the Government of India. The Employment and Unemployment Schedules are administered every five years in four sub-rounds, each with a duration of three months.[4] An equal number of households are allotted for survey during each of these four sub-rounds. We use the NSSO surveys for the years 1983, 1988, 1993, and 1999, which are the only years for which data is electronically available. The data set consists of a time-series of cross-sections since different households are surveyed every year. Households are selected via stratified random sampling.[5] The NSSO survey includes

[3]India's education system consists of primary (grades 1-5), middle (grades 6-8), secondary (grades 9- 10), and higher secondary (grades 11-12) education. Primary education is a shared responsibility of state and central governments though state governments are the main actors responsible for the allocation of educational inputs at the local level. The majority of primary schools are public schools funded by state governments. Private schools are either aided or unaided. Aided private schools are privately managed but are financed, almost exclusively, by state governments.

[4]The four sub-rounds are from July to September, October to December, January to March, and April to June.

[5]The survey covers the entire Indian Union except for certain inaccessible regions. Villages within a district are selected on the basis of their accessibility. For example, in the 1999 survey, the entire Ladakh and Kargil districts of Jammu and Kashmir, interior villages of Nagaland located beyond 5 kilometers

household and individual level data - household size and composition, social group, religion, income, assets, indebtedness, demographic variables (age, gender, marital status), education participation and attainment, and a detailed employment section on principle and subsidiary activities (industry, occupation, type and amount of income earned, and intensity of each activity).

## IV EMPIRICAL ANALYSIS

In this section we outline our empirical analysis to examine whether or not children are less likely to work and more likely to attend school in response to higher returns to education. We expect returns to education to lower child labor and increase schooling primarily via the following mechanism: parents' expectations of the future returns to investing in their children's education affect their present educational investments in their children. If present returns capture future returns to education then parents' decisions to send their children to work or school could respond to present economic returns to education.

### 1. Estimating Returns to Education

We first estimate separate earnings regressions for males and females in each Indian state (25 states and 6 union territories) for four years (1983, 1988, 1993, and 1999). Using data for the adult population aged 15 years and above, we estimate earnings regressions after correcting for selection bias using the method developed by Bourguignon et al.

of a bus route, and some inaccessible villages of Andaman and Nicobar Islands were excluded. The number of sample households surveyed within a village or town is chosen on the basis of its population. Households are first listed and then divided into two groups, affluent and non-affluent households, based on monthly expenditure levels (urban) and ownership of certain items (rural). A fixed number of households within each group are then randomly selected.

(2001) since non-zero wages are reported for only a sub-sample, i.e. individuals engaged in regular salaried or wage employment. If the selection of this sub-sample of individuals is random, then the estimates of an ordinary least squares earnings regression will be consistent and unbiased. If, however, the selection of this sub-sample is systematic - i.e. the error terms in the selection regression and the earnings regression are correlated - then ignoring the non-random nature of the sample will introduce a selection bias.[6] A multinomial logit model is used to estimate the selection process, which is modeled as having four possible outcomes: (1) non-participation in the labor market, (2) unemployment, (3) self-employment, and (4) wage employment. The selection bias correction terms are calculated from the selection regression and included in the earnings regression to correct for the selection bias.[7]

Consider the following equations for the earnings regression (Equation 1a) and the selection process into wage employment (Equation 1b):[8]

$$y_s = x_s\beta_s + \mu_s \tag{1a}$$

$$y_s^* = z_s\gamma_s + \eta_s \tag{1b}$$

where $y_s$ is earnings (the outcome variable) and $y_s^*$ is employment status (the selection variable) and $s$ is a categorical variable representing an individual's choice between $M$ alternatives, $s = 1, ..., M$. The variables $x_s$ and $z_s$ are exogenous, where $x_s$ is a subset of $z_s$ in order to identify the earnings equation.[9] The error term in the earnings regression, $\mu_s$, has $E(\mu_s|x, z) = 0$ and $V(\mu_s|x, z) = \sigma^2$.

[6]See Kingdon & Unni (1998) and Duraiswamy (2000) for similar studies on the Indian labor market.

[7]We include the details of the correction for selection bias in the Appendix.

[8]The $i$ subscript for individuals is suppressed.

[9]The appropriate identifying variables as suggested by labor supply theory are an exogenous source of non-labor income to capture household need and variables such as parent's education to capture family background. In the absence of data on non-labor income and parent's education, alternate identifying

To obtain consistent estimates of $\beta_4$, since the observed outcome belongs to category $s = 4$, Bourguignon et al. (2001) propose estimating the following model:

$$y_4 = x_4\beta_4 + \lambda + \nu_4 \tag{2}$$

where $\lambda$ consists of the selection bias correction terms and its coefficients and is defined as:

$$\lambda = \sigma_4 \left[ \tilde{\rho}_4 m\left(P_4\right) + \sum_{s<4} \tilde{\rho}_s \frac{P_s}{\left(P_s - 1\right)} m\left(P_s\right) \right] \tag{3}$$

and the error term $\nu_4$ is orthogonal to all other terms on the RHS and has zero expectation.[10]

Earnings regressions are estimated using a standard semi-logarithmic specification following Mincer (1970):

$$\ln y_4 = x_4\beta_4 + \lambda + \nu_4 \tag{4}$$

Earnings regressions are estimated separately for males and females in each of 31 states and 4 years. This gives us a total of 248 earnings regressions (2 x 31 x 4). The return to education level $e$ for gender $g$ in state $j$ and year $t$ is calculated as:

$$Return_{egjt} = \beta_{egjt} - \beta_{e-1,gjt} \tag{5}$$

variables have been used in this analysis. Household need is captured by the total area of land owned by the household, whether or not the individual is married, and the size of the household. These three variables are expected to affect participation in wage employment but not wages earned. The variables included in $x_s$ are four dummies to capture an individual's highest level of education (primary, middle, high school, or college, where the omitted category is no education), an individual's age and age-square, dummies for an individual's caste (low-caste/high-caste), religion (Muslim/non-Muslim), and sector (urban/rural), three season dummies (the omitted season is from July to September) to capture when the individual was surveyed, and the local unemployment rate. The variables included in $z_s$ consist of all those in $x_s$ and the total area of land possessed, whether or not the individual is married, and the household size.

[10] Refer to Equation 25 in the Appendix for details.

where $\beta_{egjt}$ is the coefficient for the dummy for education level $e$ for gender $g$ in state $j$ and year $t$ in the earnings regression. The subscript $e$ represents primary, middle, high school, and college education ($e = \{p, m, h, c\}$)[11], gender $g$ can be male or female, state $j$ represents India's 31 states, and $t$ represents four years (1983, 1988, 1993, and 1999). The rate of return to education level $e$ captures the additional log of hourly wages earned by an individual with education level $e$ compared to an individual with education level $(e - 1)$, per year of education level $e$, and is calculated as:

$$Rate_{egjt} = \frac{Return_{egjt}}{Years_e} \tag{6}$$

where $Years_e$ represents the number of years required to complete education level $e$ (five years for primary school, 3 years for middle school, four years for high school, and 3 years for college).

## 2. Returns to Education, Child Labor, & Schooling

We estimate participation in child labor and schooling using the rates of return to primary and middle school as the key independent variables for boys and girls aged 5 to 14 years. The returns to education capture both inter-state and inter-temporal variation. Household- and individual-level controls are included as well as year and state dummies. Because aggregate variables (returns to education) are used to estimate individual outcomes (participation in child labor and schooling), the standard errors are corrected for clustering at the year-state level (Moulton 1990).

Two points should be noted. First, we estimate the impact of *present* rather than *expected* rates of return to education on child labor and schooling. In the absence of

[11] High school consists of secondary school (grades 9 and 10) and higher secondary school (grades 11 and 12).

a measure of expected returns, present returns to education represent some signal of returns to education in the future. Second, rates of return to education not only in a child's state of residence but also in other states could affect his participation in child labor and schooling. Even though inter-state migration is relatively low in India (due to language barriers), education provides individuals with greater mobility in labor markets. Yet, returns to education in one's own state may be the only signal individuals have of employment opportunities for educated workers. An extension to our analysis could include the rates of returns to education not only in one's own state but also in neighboring states as explanatory variables.

Because the dependent variables for participation in child labor and schooling are both binary, we estimate binary probit models. The probit model assumes that there is a latent variable $y^*_{ikjt}$ that can be expressed as a linear function of variables that affect the probability of participation in child labor (schooling). This expression can be written as:

$$y^*_{ikjt} = \beta X_{ikjt} + \varepsilon_{ikjt} \tag{7}$$

where $X_{ikjt}$ is a set of explanatory variables for child $i$ in household $k$, state $j$, and year $t$, $\beta$ is the vector of coefficients that are estimated, and $\varepsilon_{ikjt}$ is an error term. The latent variable $y^*_{ikjt}$ is unobservable and instead a dummy variable is defined as $y_{ikjt} = 1$ if a child participates in child labor (attends school) and zero otherwise:

$$y_{ikjt} = \begin{cases} 1 & \text{if } y^*_{ikjt} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

The probit model assumes that the error term $\varepsilon_{ikjt}$ is distributed according to the cumulative normal distribution function. Therefore, the probability of a child participating in child labor (attending school) $P_{ikjt}$ can be written as:

$$P_{ikjt} = \text{Prob}\left(y_{ikjt} = 1\right) = \frac{1}{\sqrt{2\Pi}} \int_{-\infty}^{\beta X_{ikjt}} e^{-0.5t^2} dt \tag{9}$$

where $t$ is a standardized normal variable. Maximum likelihood estimation produces coefficient estimates.

## 3. Variables

### 3.1. Dependent Variables - Child Labor And Schooling

Our sample includes children aged 5 to 14 years to adhere to the ILO's definition of child labor. Children working in the market or household enterprise and those engaged in domestic duties are defined as child laborers for the purpose of this analysis.[12] Children who attend an educational institution are defined as attending school.

The dependent variable $ChildLabor - ftpt_{ikjt}$ reflects a child's employment status and equals 1 if he/she is reported as working full time or part time during the past 7 days and 0 otherwise.[13] The dependent variable $School - ftpt_{ikjt}$ reflects a child's school enrollment status and equals 1 if the child attended school full time or part time during the past 7 days and 0 otherwise. The Appendix includes Table 5 which describes all the variables and Table 6 which provides descriptive statistics.

[12] Regression results don't vary significantly when children engaged in domestic work are excluded from the definition of child labor (see Section 2.1.). We include children engaged in domestic duties as child laborers because domestic duties constitute 'work' rather than 'leisure'. Domestic work includes mostly cooking, cleaning, and taking care of younger siblings.

[13] Where $i$ indexes the $I$ children in our sample, $k$ indexes the $K$ households, $j$ indexes the $J$ states, and $t$ indexes the year.

### 3.2. Independent Variables

Our key independent variables are the rates of return to primary and middle school. $Rate_{egjt}$ represents the rate of return to education level $e$ ($e = \{primary, middle\}$) for gender $g$ (male or female), state $j$, and year $t$. The rate of return to education level $e$ captures the additional log of hourly wages earned by an individual with education level $e$ compared to an individual with education level $(e - 1)$, per year of education level $e$.

The control variables in the empirical estimations can be divided into three categories - household demographic characteristics, household economic conditions, and individual child-specific controls. Year dummies and state dummies are included to capture time-variant and state-specific effects. Also, season dummies are included to capture when the individual was surveyed.[14]

Household demographic characteristics include the number of children in the household ($Children_{kjt}$), four dummies each to capture the father's education level ($F - Primary$, $F - Middle$, $F - High$, and $F - College$) and the mother's education level ($M - Primary$, $M - Middle$, $M - High$, and $M - College$), and dummy variables that capture whether the household is urban ($Urban_{kjt}$), low-caste ($Lowcaste_{kjt}$), and Muslim ($Muslim_{kjt}$).[15] The number of children in the household is included to capture the idea that families with more children have fewer resources to educate each child, in other words the quantity-quality trade-off. The education levels of the father and

[14]The omitted year is 1983, the omitted state is Delhi, the nation's capital, and the omitted season is $Season_1$, from July to September. The other seasons are $Season_2$ from October to December, $Season_3$ from January to March, and $Season_4$ from April to June.

[15]Only households where a father and mother are both present are included in our sample to allow us to estimate the impact of both the father's and mother's education on participation in child labor and schooling. An alternative is to include all households and examine the impact of the education level and gender of the household head on child labor and child schooling. The omitted category for the parent's education dummies is less than primary or no formal education.

mother are included because parents with higher education have greater value for education and are more likely to educate their children than uneducated parents. Work and school decisions for children might be considerably different for those in urban and rural regions. Agricultural activities in rural areas might make children more likely to work on the household farm. We include low-caste and Muslim dummies to capture possible discrimination against these groups.

Since poverty and credit constraints have been shown to be the major causes of child labor, we control for household economic conditions and include the log of household monthly per capita consumption expenditure ($LogExpenditure_{kjt}$), adjusted to 1988 Rupees, a dummy variable to indicate whether or not the household owns land ($Asset_{kjt}$), and a dummy variable to indicate whether or not the child's mother works outside the household ($WorkingMother_{kjt}$).[16] Wealthier households are more likely to send their children to school rather than work. Ownership of assets indicates that a household is relatively wealthy and should decrease the likelihood of child labor and increase the likelihood of schooling. However, household ownership of land, especially in rural areas, could increase a child's likelihood of working because children are more likely to be engaged in agricultural activities (seasonal or full time) if their parents own and cultivate land. When the mother works outside the household, a child is more likely to be engaged in domestic chores like cooking and taking care of younger siblings, especially in the case of female children. On the other hand, if the mother works, the

[16] We face several problems with the expenditure variable. First, household monthly per capita consumption expenditure ($LogExpenditure_{kjt}$) is endogenous since it includes wages earned by children in calculating household expenditure. Second, household expenditure is calculated using an abbreviated list of items in 1999 compared to the three previous years. Therefore household expenditure is lower in 1999 compared to 1983, 1988, and 1993. We exclude this variable as an explanatory one as a robustness check (see Section 2.3.) and find that our results remain robust.

household could be less dependent on earnings from child labor, making child labor less likely and schooling more likely.

Individual child-specific controls include the child's age ($Age_{ikjt}$), the square of his/her age ($Agesq_{ikjt}$), and a gender dummy ($Male_{ikjt}$). In most empirical studies on child labor it has been found that older children are more likely to work than younger children and that this effect diminishes with a child's age. Older children are more likely to work because they tend to be more productive than younger children and therefore earn higher wages than younger children. Moreover, older children are sent to work to support younger siblings. In many developing countries, educating sons are given priority over educating daughters. In India, traditional gender roles still persist, even though these are becoming weaker. A boy's education improves his income-earning potential while a girl's education is often considered worthwhile only because it improves her marriage prospects.

We include interactions of all the independent variables with the gender dummy to incorporate different effects of each independent variable on participation in child labor and schooling for boys and girls.

## V RESULTS

### 1. Overall Significance

Before discussing results of individual variables, some indication of the overall predictive performance of the model is useful. Table 1 reports results of the likelihood ratio test for the restricted and unrestricted regressions.[17] The likelihood ratio test results indicate

[17]The restricted regression includes all the independent variables discussed in Section 3.2. except the rates of return to primary and middle school while the unrestricted regression includes the rates of return to primary and middle school. The likelihood ratio (LR) test has the following null and alternate

that the rates of return to primary and middle school are significant determinants of participation in child labor and schooling for all groups of children.

## 2. Rates of Return to Education

Tables 7 and 8 in the Appendix report marginal effects and robust standard errors for the binary probit models for participation in child labor and schooling after correcting the standard errors for clustering at the year-state level. The impact of the rates of return to education on participation in child labor and schooling are summarized in Table 2. The coefficient for boys is calculated as the sum of the coefficient for all children and the interaction term with the male dummy. The significance level for boys is based on the Wald test with the null hypothesis that the sum of these coefficients is zero.

We find a positive and significant relationship between increases in the rates of return to primary and middle schooling and declines in child labor. The magnitude of this relationship is large. For girls, a 1% increase in the middle to primary school wage ratio per year of middle school is associated with a 10 percentage point decline in child labor. For boys, a 1% increase in the primary to no school wage ratio per year of primary school is associated with a 44 percentage point decline in child labor and a 1% increase in the middle to primary school wage ratio per year of middle school is associated with a 5 percentage point decline in child labor.[18]

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hypotheses:

$$H_O : \beta_e = 0, H_A : \beta_e \neq 0$$

for $e = \{p, m\}$. In other words, the null hypothesis is that the restricted regression is correct while the alternate hypothesis is that the unrestricted regression is correct. The LR test statistic is calculated as $2\left(LogLikelihood_{UR} - LogLikelihood_{RR}\right)$, which has a chi-square distribution. With 4 degrees of freedom (4 restrictions) the critical chi-square is 13.28 at the 1% level of significance. A *** indicates that the LR test statistic is greater than the critical chi-square value and therefore the null hypothesis is rejected at the 1% level of significance.

[18]The coefficient on the rate of return to education level $e$ measures the change in probability that

We find a positive and significant relationship between increases in the rates of return to primary and middle schooling and increases in schooling for boys. A 1% increase in the primary to no school wage ratio per year of primary school is associated with an almost 47 percentage point increase in schooling while a 1% increase in the middle to primary school wage ratio per year of middle school is associated with a 13 percentage point increase in schooling amongst boys.

The gender differential observed in Table 2 can perhaps be attributed to the persistence of traditional gender roles in India. Though womens' participation in the work force has been steadily increasing over time, conservative and orthodox beliefs persist in many regions in India. While education is expected to improve a boy's income-earning potential, for many girls education is expected to improve only her marriage prospects. Also, while sons are expected to provide for their parents, daughters are not. Therefore, boys' participation in both child labor and schooling respond strongly to higher benefits to their education in the labor market.

## 3. Year Dummies

Coefficients of the year dummies capture trends in participation in child labor and schooling for boys and girls. As Table 3 shows, child labor and schooling are both higher in 1988, 1993, and 1999, compared to the omitted year, 1983. From 1988 onwards, child labor has been decreasing and schooling increasing. The coefficient for boys is

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a child works (attends school) with a 1% increase in the wage ratio of education level $e$ to education level $e-1$ per year of education level $e$:

$$Coefficient = \frac{\partial P}{\partial Rate_e} = \frac{\partial P}{\partial \left( \frac{\ln wage_e - \ln wage_{e-1}}{Years_e} \right)} = \frac{\partial P}{\frac{\partial \ln \left( \frac{wage_e}{wage_{e-1}} \right)}{Years_e}} \tag{10}$$

where $P$ is the probability that a child works (attends school).

calculated as the sum of the coefficient for all children and the interaction term with the male dummy. The significance level for boys is based on the Wald test with the null hypothesis that the sum of these coefficients is zero.

The year dummies capture a decreasing trend in child labor and an increasing trend in schooling between 1988 and 1999. These trends are significantly different for boys and girls. Between 1988 and 1999, child labor has declined by 8 (4) percentage points and schooling has increased by 14 (10) percentage points amongst girls (boys). The year dummies could be capturing changes in education policies, for example free primary education and the provision of school meals. Perhaps education policies have a stronger effect on girls rather than boys because the base is lower for girls - i.e. child labor was higher and schooling was lower amongst girls to begin with. Therefore, there is more scope to lower child labor and increase schooling amongst girls than boys. Cultural changes could also be playing a role in increasing schooling, especially amongst girls.

The trends captured by the year dummies are reflected in actual changes in the proportion of children participating in child labor and schooling between 1988 and 1999. Table 4 reports these changes.[19]

## 4. Control Variables

The control variables have the expected signs (except for a child's age) and are mostly significant at the 1% level.

We find that a higher number of children in the household makes a child more likely

[19]The figures reported are the total number of hours spent working (market work, household enterprise work, and domestic work) or attending school as a percentage of the total number of hours spent in all activities (including hours spent doing nothing - i.e. neither work nor school) in each group (boys or girls). The figures remain almost identical if we calculate the number of children engaged in work or school as a proportion of all children in each group (boys or girls).

to work. However, the number of children in a household is not a significant determinant of a child's participation in school. All children are less likely to work and more likely to attend school if their father and/or mother have completed primary, middle, high school or college. Two observations are interesting. First, the father's education has a stronger impact on childrens' participation in work and school than the mother's education. Second, both parents' education has a stronger impact on participation in child labor and schooling for girls than for boys. Thus, our results indicate that parental education increases educational investments in girls more so than in boys.

Children residing in urban regions are less likely to work and more likely to attend school. This urban bias is stronger for girls than for boys. In other words, the difference in participation in child labor and schooling between urban and rural girls is much larger than the difference between urban and rural boys. Being lowcaste or Muslim increases the likelihood of child labor and decreases the likelihood of attending school for both boys and girls, reflecting the widespread discrimination against these groups.

All children are more likely to work and less likely to attend school if his or her mother works outside the home. This effect is particularly strong for girls and can be explained by the fact that working mothers often take their children, especially daughters, with them to work or make their daughters perform household chores while they work. A higher log of per capita monthly household expenditure makes a child less likely to work and more likely to attend school. Ownership of land has a negative impact on boys' participation in child labor and a positive impact on both boys' and girls' participation in schooling.

There is a U-shaped (inverted-U-shaped) relationship between age and child labor (schooling) - a child is less (more) likely to work (attend school) from the ages of 5 to

9 and then more (less) likely to work (attend school) from the ages of 9 to 14. In most of the empirical literature on child labor, older children are found to be more likely to work.

We find that boys are more likely to work than girls. Thus, after controlling for the indirect effect that being male has on participation in child labor and schooling, via household and individual characteristics, the direct effect of being male is the opposite of what we expected.

## VI ROBUSTNESS

Table 2 shows the empirical evidence we find to validate the main predictions of our theory for the case of India. In response to higher rates of return to education child labor falls and schooling increases. In this section we show that our results are robust to a variety of specifications and robustness checks.

### 1. Overcorrection of Standard Errors

The results reported in Tables 2 and 3 are obtained after correcting the standard errors for clustering at the year-state level. According to Moulton (1990), when estimating the impact of aggregate variables on individual outcomes, unobservable characteristics at the aggregate level can affect all observations within a cluster and inflate the statistical significance of the aggregate variable. In our case, the rates of return to primary and middle school are calculated for each state in each year. Therefore, correlations within each year-state combination must be accounted for. Correcting the standard errors for clustering at the year-state level provide us with an estimator of the variance covariance matrix which is consistent in the presence of any correlation pattern within states over time. One drawback to this procedure, however, is that the standard errors are over-corrected. The over-correction occurs because all the intra-cluster correlations (i.e. the correlation within every year-state combination) are assumed to be significant. Without this correction, all intra-cluster correlations are assumed to be insignificant. In reality, correlations within some clusters are significant while others are not. Therefore, the true variance covariance matrix lies in-between these two extreme cases.

Without correcting the standard errors for clustering at the year-state level, the rates of return to education are found to be far more significant determinants of participation in child labor and schooling. The results are reported in Tables 9 and 10 in the Appendix and summarized in Table 5.

When we don't correct the standard errors for clustering at the year-state level for both boys and girls, participation in full time or part time work and school respond strongly to changes in the rates of return to both primary and middle school. The results reported in Table 5 represent one extreme assumption (that the intra-cluster correlation within every cluster is insignificant) while those presented in Table 2 represent the other extreme (that the intra-cluster correlation within every cluster is significant). The true variance covariance matrix lies in between these two extreme cases.

## 2. Other Robustness Checks

### 2.1. Children Engaged in Domestic Chores

In this section, we exclude children engaged in domestic chores from our definition of child labor and include only those engaged in market or household enterprise work. We do this in order to keep to the ILO's definition of child labor. The results are reported in Table 11 in the Appendix and summarized in Table 6. We find a significant decrease in child labor amongst girls brought about by higher rates of return to middle school and a significant decrease in child labor amongst boys in response to higher rates of return to primary school.

### 2.2. Full Time Work, Full Time School, and Part Time Work and School

To test the robustness of the empirical results, we use three different specifications of child labor and schooling. The dependent variable $ChildLabor - ft_{ikjt}$ equals 1 if a child is reported as working full time during the past 7 days and 0 otherwise. Similarly, $School - ft_{ikjt}$ equals 1 if a child attended school full time during the past 7 days and 0 otherwise. $ChildLabor - School - pt_{ikjt}$ equals 1 if a child was engaged in both work and school part time during the past 7 days and 0 otherwise. Tables 12, 13, and 14 in the Appendix report marginal effects for the binary probit models for participation in child labor and schooling while the results are summarized in Table 7. We find a significant decrease in part-time work and school amongst girls as a result of higher rates of return to middle school. In response to higher rates of return to primary school, boys are less likely to engage in full time work, more likely to engage in full time shcool, and less likely to engage in part-time work and school.

### 2.3. Endeogeneity of Per Capita Household Expenditure

As an additional robustness check, we exclude the variable $LogExpenditure_{kjt}$ because per capita household expenditure could be endogoenous. In other words, a child's participation in work could raise household income, household expenditure, and thereby per capita household expenditure. Omitting this variable from the right hand side does not significantly change the results. Tables 15 and 16 in the Appendix report the results, which are summarized in Table 8. Higher rates of return to middle school lower participation in child labor amongst girls while higher rates of return to primary school lower child labor and increase schooling amongst boys.

### 2.4. Including the Rates of Return to High School & College

One can argue that in deciding whether to send their children to primary or middle school or to work, parents respond to the returns to high school and college as well. This argument is based on the fact that a child's completion of primary and middle school is necessary before he or she attends high school or college. To check the validity of this argument we include the rates of return to high school and college as determinants of participation in child labor and schooling. The results are reported in Tables 17 and 18 in the Appendix and summarized in Table 9. We find that the rates of return to high school and college are statistically insignificant in determining participation in child labor and schooling. Moreover, when the rates of return to high school and college are included as explanatory variables, we find a negative and significant association between the rates of return to primary school and child labor amongst boys and a positive and significant association between the rates of return to primary school and schooling amongst boys.

## VII CONCLUSION

The empirical results presented here indicate that higher rates of return to education decrease child labor and increase education amongst boys and decrease child labor amongst girls. The rate of return to primary school has a strong impact on boys' participation in child labor and schooling while girls' participation in child labor responds to changes in the rate of return to middle school. In light of these results, policies that raise the returns to education can have a beneficial impact on human capital investments in India by providing parents with the correct incentives to educate their children. Such policies can be used to complement anti-child-labor and compulsory education laws.

One way of raising the returns to education is by increasing the demand for skilled labor via the creation of skilled-labor-intensive employment opportunities. Amongst the policies that can be used to expand employment opportunities for educated workers and raise the benefits to obtaining an education are the liberalization of trade and investment. Rather than lower the demand for skilled labor, as the Stolper-Samuelson theorem predicts, trade liberalization in developing countries can increase the demand for skilled labor via the transfer of skill-biased technology. A greater demand for skilled labor can raise the returns to education and foster greater investment in human capital. Without incentives for firms to invest in skill-biased capital, however, trade liberalization may be insufficient to generate skill-biased investment by firms.

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Table 1: Likelihood-Ratio Test

| **Dependent Variable** | **LR Test Statistic** |
|---|---|
| Work - full time or part time | 602.24*** |
| School - full time or part time | 353.44*** |

***Significant at 1%.

Table 2: Rates of Return to Education, Child Labor, and Schooling

| | Work | School |
|---|---|---|
| **Girls** | | |
| Primary | -0.0358 | -0.1031 |
| Middle | -0.1014* | 0.0174 |
| **Boys** | | |
| Primary | -0.4400*** | 0.4662*** |
| Middle | -0.0516 | 0.1342*** |

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Robust standard errors are corrected for clustering at the year-state level.

Table 3: Year Dummies, Child Labor, and Schooling

| | Work | School |
|---|---|---|
| **Girls** | | |
| Year88 | 0.2824*** | 0.0491*** |
| Year93 | 0.2284*** | 0.1432*** |
| Year99 | 0.2021*** | 0.1903*** |
| 1988-1999 | -0.0803 | 0.1412 |
| **Boys** | | |
| Year88 | 0.2832*** | 0.0305*** |
| Year93 | 0.2304*** | 0.1354*** |
| Year99 | 0.2423*** | 0.1355*** |
| 1988-1999 | -0.0410 | 0.1050 |

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Robust standard errors are corrected for clustering at the year-state level.

Table 4: Observed Child Labor and Schooling (%), 1988-1999

| | Work | School |
|---|---|---|
| **Girls** | | |
| 1988 | 44.42 | 55.23 |
| 1993 | 31.70 | 68.00 |
| 1999 | 29.14 | 70.63 |
| 1988-1999 | -15.28 | 15.40 |
| **Boys** | | |
| 1988 | 31.94 | 67.54 |
| 1993 | 21.66 | 78.02 |
| 1999 | 21.65 | 78.03 |
| 1988-1999 | -10.29 | 10.49 |

The change in child labor and schooling is in percentage points.

Table 5: Rates of Return to Education, Child Labor, and Schooling: Without Correcting Standard Errors for Clustering

| | Work | School |
|---|---|---|
| **Girls** | | |
| Primary | -0.0358** | -0.1031*** |
| Middle | -0.1014*** | 0.0174* |
| **Boys** | | |
| Primary | -0.4400*** | 0.4662*** |
| Middle | -0.0516*** | 0.1342*** |

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Standard errors are not corrected for clustering at the year-state level.

Table 6: Rates of Return to Education & Child Labor: Excluding Children Engaged in Household Chores from Child Labor

| | Work |
|---|---|
| **Girls** | |
| Primary | -0.0687 |
| Middle | -0.1108*** |
| **Boys** | |
| Primary | -0.2885** |
| Middle | -0.0124 |

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Standard errors are corrected for clustering at the year-state level.

Table 7: Rates of Return to Education, Full Time Work, Full Time School, & Part Time Work & School

| | Full Time Work | Full Time School | Part Time Work & School |
|---|---|---|---|
| **Girls** | | | |
| Primary | 0.0147 | -0.0498 | -0.0011 |
| Middle | -0.0488 | 0.0710 | -0.0011*** |
| **Boys** | | | |
| Primary | -0.2710** | 0.6581*** | -0.0022* |
| Middle | -0.0681 | 0.1147 | 0.0002 |

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Standard errors are not corrected for clustering at the year-state level.

Table 8: Rates of Return to Education, Child Labor, & Schooling: Excluding Household Expenditure

| | Work | School |
|---|---|---|
| **Girls** | | |
| Primary | -0.0402 | -0.0937 |
| Middle | -0.1021* | 0.0195 |
| **Boys** | | |
| Primary | -0.4482*** | 0.4852*** |
| Middle | -0.0473 | 0.1280 |

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Standard errors are not corrected for clustering at the year-state level.

Table 9: Rates of Return to Education & Child Labor: Including Rates of Return to High School & College

| | Work | School |
|---|---|---|
| **Girls** | | |
| Primary | -0.0145 | -0.0755 |
| Middle | -0.0861 | 0.0300 |
| High | 0.0342 | 0.0307 |
| College | 0.0244 | 0.0184 |
| **Boys** | | |
| Primary | -0.5386*** | 0.4835*** |
| Middle | -0.0386 | 0.1418 |
| High | 0.1557 | -0.0285 |
| College | 0.1461 | -0.0009 |

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Standard errors are not corrected for clustering at the year-state level.

# A APPENDIX

## 1. CORRECTION OF WAGE EQUATIONS FOR SAMPLE SELECTION BIAS

Consider the following equations for the earnings regression (Equation 11a) and the selection process into wage employment (Equation 11b):[20]

$$y_s = x_s\beta_s + \mu_s \tag{11a}$$

$$y_s^* = z_s\gamma_s + \eta_s \tag{11b}$$

where $y_s$ is earnings (the outcome variable) and $y_s^*$ is employment status (the selection variable) and $s$ is a categorical variable representing an individual's choice between $M$ alternatives, $s = 1, ..., M$. The variables $x_s$ and $z_s$ are exogenous, where $x_s$ is a subset of $z_s$ in order to identify the earnings equation. The error term in the earnings regression, $\mu_s$, has $E\left(\mu_s|x, z\right) = 0$ and $V\left(\mu_s|x, z\right) = \sigma^2$.

The outcome variable, $y_s$, is observed if and only if the category $s$ is chosen, which happens when

$$y_s^* > \max_{j \neq s}\left(y_j^*\right) \tag{12}$$

Equation 12 is equivalent to:

$$z_s\gamma_s > \varepsilon_s \tag{13}$$

where,

$$\varepsilon_s = \max_{j \neq s}\left(y_j^* - \eta_s\right) \tag{14}$$

Assume now that the $\eta$'s are independent and identically Gumbel distributed. Thus, their cumulative and density functions are respectively $G\left(\eta\right) = \exp\left(-e^{-\eta}\right)$ and $g\left(\eta\right) =$

[20] The $i$ subscript for individuals is suppressed.

$\exp\left(-\eta - e^{-\eta}\right)$. As shown by McFadden (1974), this specification leads to the multinomial logit model with:

$$P\left(y_s^*\right) = P\left(z_s\gamma_s > \varepsilon_s\right) = \frac{\exp z_s\gamma_s}{\sum\limits_j \exp z_j\gamma_j} \tag{15}$$

where $P\left(y_s^*\right)$ is the probability that category $s$ was chosen. Based on this expression, maximum likelihood estimates of the $\gamma_j$'s can be easily obtained.

Because the error terms $\mu_s$ and $\eta_s$'s are correlated, ordinary least squares estimates of $\beta_s$ are inconsistent. To obtain consistent estimates of $\beta_4$, since the observed outcome belongs to category $s = 4$, Bourguignon et al. (2001) propose estimating the following model. Define the following standard normal variables for $s = 1, ..., 4$:

$$\eta_s^* = J\left(\eta_s\right) = \Phi^{-1}\left(G\left(\eta_s\right)\right) \tag{16}$$

where $\Phi$ is the standard normal distribution function. For every $s$, assume that the expected values of $\mu_4$ and $\eta_s^*$ are linearly related. If $\tilde{\rho}_s$ is the correlation coefficient between $\mu_4$ and $\eta_s^*$, i.e. $\tilde{\rho}_s = \frac{\sigma_{4\eta_s^*}}{\sigma_4\sigma_{\eta_s^*}}$ (where $\sigma_{4\eta_s^*}$ is the correlation between $\mu_4$ and $\eta_s^*$, $\sigma_4$ is the standard deviation of $\mu_4$, and $\sigma_{\eta_s^*}$ is the standard deviation of $\eta_s^*$) then $\mu_4$ can be expressed as the following linear combination of the $\eta_s^*$'s:

$$\mu_4 = \sigma_4 \sum_s \tilde{\rho}_s\eta_s^* + \omega_4 \tag{17}$$

where $\omega_4$ is an error term which is orthogonal to all the $\eta_s^*$'s and $E\left(\omega_4\right) = 0$. This expression uses the fact that the $\eta_s^*$'s are independent from each other. In order to make the earnings regression, 11a, estimable through ordinary least squares for $s = 4$, it is necessary to know the expectation of $\mu_4$ conditional on the fact that category $s = 4$ is observed. Using the preceding relationships and the independence of the error term $\omega_4$ from the $\eta_s^*$'s gives:

$$E\left(\mu_4|y_4^* > \max_{j\neq 4}\left(y_j^*\right)\right) = \sigma_4 \sum_s \tilde{\rho}_s E\left(\eta_s^*|y_4^* > \max_{j\neq 4}\left(y_j^*\right)\right) \tag{18}$$

with

$$E\left(\eta_s^*|y_4^* > \max_{j\neq 4}\left(y_j^*\right)\right) = \int J\left(\eta_s\right) f\left(\eta_s|y_4^* > \max_{j\neq 4}\left(y_j^*\right)\right) d\eta_s \tag{19}$$

Bourguignon et al. (2001) derive the conditional densities $f\left(\eta_s|y_4^* > \max_{j\neq 4}\left(y_j^*\right)\right)$. It follows from there that for $\eta_4^*$,

$$E\left(\eta_4^*|y_4^* > \max_{j\neq 4}\left(y_j^*\right)\right) = \int J\left(\eta_4\right) g\left(\eta_4 + \log P_4\right) d\eta_4 \tag{20}$$

where $P_s = P\left(y_s^*\right)$ is the probability that category $s$ was chosen. Let $v = \eta_4 + \log P_4$. Then,

$$E\left(\eta_4^*|y_4^* > \max_{j\neq 4}\left(y_j^*\right)\right) = \int J\left(v - \log P_4\right) g\left(v\right) dv \tag{21}$$

For $\eta_s^*$, $s \neq 4$,

$$\begin{aligned} E\left(\eta_s^*|y_4^* > \max_{j\neq 4}\left(y_j^*\right)\right) &= \int J\left(\eta_s\right) \frac{1}{\left(1-P_s\right)} \left[g\left(\eta_s\right) - e^{-\eta_s} \exp\left(\frac{-e^{-\eta_s}}{P_s}\right)\right] d\eta_s \\ &= \frac{1}{\left(1-P_s\right)} \int J\left(\eta_s\right) g\left(\eta_s\right) d\eta_s - \frac{1}{\left(1-P_s\right)} \int J\left(\eta_s\right) e^{-\eta_s} \exp\left(\frac{-e^{-\eta_s}}{P_s}\right) d\eta_s \end{aligned} \tag{22}$$

Let $v = \eta_s + \log P_s$ and notice that $\int J\left(\eta_s\right) g\left(\eta_s\right) d\eta_s = E\left(\eta_s^*\right) = 0$. Then,

$$E\left(\eta_s^*|y_4^* > \max_{j\neq 4}\left(y_j^*\right)\right) = \frac{P_s}{\left(P_s - 1\right)} \int J\left(v - \log P_s\right) g\left(v\right) dv \tag{23}$$

For convenience, let $m\left(P_s\right) = \int J\left(v - \log P_s\right) g\left(v\right) dv, \forall s$. Substituting equations 21 and 23 into equation 18 gives:

$$E\left(\mu_4|y_4^* > \max_{j\neq 4}\left(y_j^*\right)\right) = \sigma_4 \left[\tilde{\rho}_4 m\left(P_4\right) + \sum_{s<4} \tilde{\rho}_s \frac{P_s}{\left(P_s - 1\right)} m\left(P_s\right)\right] \tag{24}$$

Replacing the error term in the earnings regression (Equation 11a) by its conditional expected value (Equation 24) and a residual term ($\nu_4$) gives:

$$y_4 = x_4\beta_4 + \sigma_4 \left[ \tilde{\rho}_4 m\left(P_4\right) + \sum_{s<4} \tilde{\rho}_s \frac{P_s}{\left(P_s - 1\right)} m\left(P_s\right) \right] + \nu_4 \tag{25}$$

where $\tilde{\rho}_s$ is the correlation coefficient between $\mu_4$ and $\eta_s^*$, i.e. $\tilde{\rho}_s = \frac{\sigma_{4\eta_s^*}}{\sigma_4 \sigma_{\eta_s^*}}$, $P_s = P\left(y_s^*\right)$ is the probability that category $s$ was chosen, $m\left(P_s\right) = \int J\left(v - \log P_s\right) g\left(v\right) dv$, $v = \eta_s + \log P_s$, and $J\left(\circ\right) = \Phi^{-1}\left(G\left(\circ\right)\right)$, for $s = 1, ..., 4$.

The error term $\nu_4$ is now orthogonal to all other terms on the RHS and has zero expectation. Because of this property ordinary least squares may now be used to provide consistent estimates of the $\beta_4$'s, $(\sigma_4\tilde{\rho}_1)$, $(\sigma_4\tilde{\rho}_2)$, $(\sigma_4\tilde{\rho}_3)$, and $(\sigma_4\tilde{\rho}_4)$.[21] The selectivity correction within the multinomial logit setup involves all correlation coefficients between the disturbance term of the earnings equation ($\mu_4$) and the disturbance terms of all categorical latent expressions ($\eta_s^*$ for $s = 1, ..., 4$).

In terms of practical implementation, the method consists of two steps. First, estimate the multinomial logit, and derive from it the predicted probabilities $\hat{P}_s$'s using the $\hat{\gamma}_s$'s. The integrals $m\left(P_s\right)$ have no analytical solution as functions of $P_s$, so they must be computed numerically. This is not a source of computational complexity, however, as it must be done only once for each observation. In the Stata ado program Bourguignon et al. (2001) compute these numerical integrals using the Gauss-Laguerre quadrature method. The abscissas and weight factors used in the program are from Davis & Polonsky (1964). Second, estimate Equation 25 by ordinary least squares.

[21] Note that in the second stage, if one is interested in the values of $\tilde{\rho}_1$, $\tilde{\rho}_2$, $\tilde{\rho}_3$, and $\tilde{\rho}_4$, full identification is provided by estimating $\sigma_4$ from the residuals of the earnings equation (Equation 11a) where $\sigma_4$ is the standard deviation of $\mu_4$. More directly, non-linear least squares may also be used.

## 2. TABLES

Table 1: Regional and Social Disparities in Literacy Rates in India, 2001

| **Region/State/Caste** | **Gender** | | |
|---|---|---|---|
| | Male | Female | Total |
| Urban | 86.42 | 72.99 | 80.06 |
| Rural | 71.18 | 46.58 | 59.21 |
| Kerala | 94.20 | 87.86 | 90.92 |
| Bihar | 60.32 | 33.57 | 47.53 |
| Scheduled Castes | 49.91 | 23.76 | 37.41 |
| Scheduled Tribes | 40.65 | 18.10 | 29.60 |
| India | 75.64 | 54.03 | 65.20 |

Source: Census of India, 2001.

Table 2: Child Labor & Education in India - A Legislative Review

| Year | Legislation | Summary |
|---|---|---|
| | Child Labor Legislation | |
| 1881 | Factories Act | Imposed minimum working age of 7 years. |
| 1922 | Factories Act | Raised minimum age for factory employment to 15 years. |
| 1923 | Mines Act | Raised minimum age for employment in mines to 13 years. |
| 1938 | Employment of Children Act | Prohibited child labor in hazardous occupations and processes. |
| 1948 | Factories Act | Lowered minimum age for factory employment to 14 years. |
| 1951 | Plantations Labor Act | Set minimum age for employment on plantations as 12 years. |
| 1952 | Mines Act | Raised minimum age for employment in mines to 15 years. |
| 1954 | Factories Act | Prohibited factory employment of adolescents under 17 years at night. |
| 1966 | Bidi & Cigar Workers Act | Set minimum age for employment in bidi or cigar factories as 14 years. |
| 1986 | Child Labor Prohibition & Regulation Act | Prohibited child labor in hazardous occupations and processes & Regulated work conditions in other jobs. |
| | Education Legislation | |
| 1950 | Article 45, Constitution | Provision of free & compulsory education for children below the age of 14. |
| 1986 | National Policy on Education | Creation of model district schools for high-achieving rural youth & Universalization of education via Operation Blackboard & Non-Formal Education. |

Source: Murphy & Welch (1991).

Table 3: Child Labor & Schooling in Indian States & Union Territories (1983-1999)

| **State/Union Territory** | **Child Labor** | | | | **Schooling** | | | |
|---|---|---|---|---|---|---|---|---|
| | 1983 | 1988 | 1993 | 1999 | 1983 | 1988 | 1993 | 1999 |
| Andhra Pradesh | 23.38 | 39.56 | 28.41 | 32.51 | 54.97 | 59.99 | 71.38 | 76.78 |
| Arunachal Pradesh | 0.00 | 50.10 | 42.73 | 54.07 | 57.14 | 48.19 | 62.75 | 55.32 |
| Assam | 9.38 | 29.07 | 41.23 | 30.68 | 60.03 | 69.52 | 77.74 | 75.89 |
| Bihar | 18.43 | 57.39 | 41.94 | 49.20 | 36.65 | 42.40 | 58.55 | 51.63 |
| Goa, Daman & Diu | 9.86 | 10.09 | 15.85 | 50.10 | 73.94 | 89.33 | 90.55 | 84.91 |
| Gujarat | 15.08 | 32.86 | 41.04 | 54.38 | 59.21 | 66.50 | 73.95 | 74.96 |
| Haryana | 18.14 | 33.45 | 19.49 | 17.33 | 55.98 | 66.30 | 80.87 | 82.73 |
| Himachal Pradesh | 11.96 | 21.88 | 15.57 | 7.42 | 69.91 | 77.71 | 87.76 | 92.75 |
| Jammu and Kashmir | 13.64 | 41.31 | 23.24 | 21.29 | 49.04 | 58.29 | 79.09 | 82.15 |
| Karnataka | 21.93 | 36.52 | 24.73 | 24.54 | 52.28 | 62.79 | 77.33 | 76.89 |
| Kerala | 5.34 | 8.89 | 6.43 | 8.13 | 88.38 | 90.60 | 95.15 | 94.78 |
| Madhya Pradesh | 19.02 | 48.07 | 37.15 | 36.92 | 45.67 | 51.69 | 65.02 | 66.70 |
| Maharashtra | 14.36 | 25.93 | 19.81 | 31.06 | 65.91 | 73.80 | 82.63 | 83.57 |
| Manipur | 3.77 | 19.16 | 15.99 | 25.58 | 57.35 | 80.57 | 88.40 | 87.50 |
| Meghalaya | 9.81 | 50.57 | 20.60 | 43.64 | 65.27 | 49.32 | 80.13 | 82.16 |
| Mizoram | 2.32 | 25.35 | 55.57 | 36.75 | 72.99 | 74.51 | 89.22 | 80.08 |
| Nagaland | 2.33 | 21.79 | 9.95 | 10.13 | 86.05 | 78.21 | 90.05 | 91.45 |
| Orissa | 20.20 | 39.98 | 34.66 | 29.58 | 47.98 | 59.61 | 66.92 | 70.74 |
| Punjab | 16.06 | 28.93 | 18.30 | 15.37 | 66.27 | 70.62 | 83.09 | 85.41 |
| Rajasthan | 26.81 | 50.90 | 37.94 | 27.85 | 41.61 | 48.85 | 61.99 | 72.04 |
| Sikkim | 11.88 | 24.06 | 9.39 | 13.78 | 77.78 | 75.78 | 92.19 | 86.33 |
| Tamil Nadu | 16.05 | 21.07 | 17.45 | 21.30 | 69.54 | 78.20 | 85.05 | 88.65 |
| Tripura | 6.92 | 32.94 | 13.49 | 12.94 | 41.71 | 66.62 | 86.67 | 87.00 |
| Uttar Pradesh | 17.87 | 50.43 | 37.87 | 33.02 | 41.60 | 49.35 | 63.72 | 69.39 |
| West Bengal | 19.29 | 39.77 | 33.05 | 27.26 | 56.75 | 59.93 | 72.13 | 75.00 |
| Andaman & Nicobar Islands | 4.53 | 12.87 | 15.09 | 22.69 | 82.28 | 86.94 | 84.99 | 77.31 |
| Chandigarh | 8.07 | 13.28 | 8.00 | 9.32 | 77.31 | 86.72 | 91.20 | 91.68 |
| Dadra & Nagar Haveli | 26.06 | 58.96 | 49.08 | 87.07 | 41.35 | 41.04 | 50.55 | 64.56 |
| Delhi | 8.09 | 11.12 | 16.08 | 14.71 | 84.86 | 88.55 | 90.71 | 88.64 |
| Lakshadweep | 0.00 | 14.72 | 1.92 | 4.88 | 85.71 | 84.26 | 98.08 | 95.12 |
| Pondicherry | 10.11 | 15.28 | 4.68 | 10.70 | 82.22 | 84.07 | 94.95 | 94.14 |
| All India | 16.76 | 37.82 | 30.18 | 31.19 | 54.60 | 61.76 | 73.39 | 74.58 |

NSSO Data, 1983, 1988, 1993, and 1999. The figures reported for child labor are the total number of hours spent working (market work, household enterprise work, and domestic work) as a percentage of the total number of hours spent in all activities (which includes hours spent doing nothing - i.e. neither work nor school) for children aged 5-14 years. The figures reported for schooling are the total number of hours spent attending school as a percentage of the total number of hours spent in all activities for children aged 5-14 years.

Table 4: Child Labor & Schooling in India (1983-1999)

| **State/Union Territory** | 1983 | 1988 | 1993 | 1999 | 83-88 | 88-93 | 93-99 |
|---|---|---|---|---|---|---|---|
| **All India** | | | | | | | |
| School | 54.58 | 61.74 | 73.35 | 74.53 | 7.17 | 11.61 | 1.18 |
| Work | 16.76 | 37.82 | 26.34 | 25.19 | 21.06 | -11.48 | -1.15 |
| | | | | | | | |
| **Urban** | | | | | | | |
| School | 72.10 | 75.88 | 83.72 | 82.87 | 3.78 | 7.84 | -0.85 |
| Work | 9.39 | 23.72 | 15.97 | 16.87 | 14.34 | -7.76 | 0.90 |
| | | | | | | | |
| **Rural** | | | | | | | |
| School | 46.00 | 54.95 | 67.33 | 69.83 | 8.95 | 12.37 | 2.51 |
| Work | 20.36 | 44.58 | 32.36 | 29.87 | 24.22 | -12.22 | -2.49 |
| | | | | | | | |
| **Male** | | | | | | | |
| School | 61.82 | 67.54 | 78.02 | 78.03 | 5.72 | 10.47 | 0.01 |
| Work | 12.21 | 31.94 | 21.66 | 21.65 | 19.73 | -10.28 | -0.01 |
| | | | | | | | |
| **Female** | | | | | | | |
| School | 46.51 | 55.23 | 68.00 | 70.63 | 8.72 | 12.77 | 2.63 |
| Work | 21.82 | 44.42 | 31.70 | 29.14 | 22.60 | -12.72 | -2.56 |

NSSO Data, 1983, 1988, 1993, and 1999. The figures reported are the total number of hours spent working (market work, household enterprise work, and domestic work) or attending school as a percentage of the total number of hours spent in all activities (which includes hours spent doing nothing - i.e. neither work nor school) for children aged 5-14 years. All changes are in percentage points.

Table 5: Description of Dependent and Independent Variables

| Variable | Description | Expected Sign CL | Expected Sign CS |
|---|---|---|---|
| **Dependent Variables** | | | |
| $ChildLabor-ftpt_{ikjt}$ | 1 if child worked full time or part time during past week, 0 otherwise | | |
| $School-ftpt_{ikjt}$ | 1 if child attended school full time or part time during past week, 0 otherwise | | |
| $ChildLabor-ft_{ikjt}$ | 1 if child worked full time during past week, 0 otherwise | | |
| $School-ft_{ikjt}$ | 1 if child attended school full time during past week, 0 otherwise | | |
| $ChildLabor\&Schooling-pt_{ikjt}$ | 1 if child worked and attended school part time during past week, 0 otherwise | | |
| **Independent Variables** | | | |
| $Rate-Primary_{gjt}$ | Rate of return to primary school | - | + |
| $Rate-Middle_{gjt}$ | Rate of return to middle school | - | + |
| $Children_{kjt}$ | Number of children | + | - |
| $F-Primary_{kjt}$ | 1 if father has primary education, 0 otherwise | - | + |
| $F-Middle_{kjt}$ | 1 if father has middle education, 0 otherwise | - | + |
| $F-High_{kjt}$ | 1 if father has high school education, 0 otherwise | - | + |
| $F-College_{kjt}$ | 1 if father has college education, 0 otherwise | - | + |
| $M-Primary_{kjt}$ | 1 if mother has primary education, 0 otherwise | - | + |
| $M-Middle_{kjt}$ | 1 if mother has middle education, 0 otherwise | - | + |
| $M-High_{kjt}$ | 1 if mother has high school education, 0 otherwise | - | + |
| $M-College_{kjt}$ | 1 if mother has college education, 0 otherwise | - | + |
| $Urban_{kjt}$ | 1 if household resides in urban region, 0 otherwise | + | - |
| $Lowcaste_{kjt}$ | 1 if household is lowcaste, 0 otherwise | + | - |
| $Muslim_{kjt}$ | 1 if household is Muslim, 0 otherwise | + | - |
| $WorkingMother_{kjt}$ | 1 if mother works outside the household, 0 otherwise | + | - |
| $LogExpenditure_{kjt}$ | Household monthly per capita consumption expenditure | - | + |
| $Asset_{kjt}$ | 1 if household owns land, 0 otherwise | - | + |
| $Age_{ikjt}$ | Child's age in years | + | - |
| $Agesq_{ikjt}$ | Square of child's age in years | | |
| $Male_{ikjt}$ | 1 if child is male, 0 otherwise | + | - |
| $Season_s$ | 1 if household surveyed during season $s$, 0 otherwise | | |
| $Year_t$ | 1 if year $t$, 0 otherwise | | |
| $State_j$ | 1 if state $j$, 0 otherwise | | |

The subscript $i$ represents each child, $k$ each household, $j$ each state, $t$ each year, $g$ each gender, and $s$ each season.

Table 6: Summary Statistics of Dependent and Independent Variables

| Variable | Mean | Standard Deviation |
|---|---|---|
| **Dependent Variables** | | |
| $ChildLabor - ftpt$ | 0.2926 | 0.4550 |
| $School - ftpt$ | 0.6522 | 0.4763 |
| $ChildLabor - ft$ | 0.2643 | 0.4409 |
| $School - ft$ | 0.6271 | 0.4836 |
| $ChildLabor\&School - pt$ | 0.0251 | 0.1564 |
| | | |
| **Independent Variables** | | |
| $Rate - Primary$ | 0.0384 | 0.0698 |
| $Rate - Middle$ | 0.0587 | 0.1514 |
| $Rate - High$ | 0.1288 | 0.1753 |
| $Rate - College$ | 0.1175 | 0.1741 |
| $Year - 83$ | 0.2726 | 0.4453 |
| $Year - 88$ | 0.2714 | 0.4447 |
| $Year - 93$ | 0.2212 | 0.4151 |
| $Year - 99$ | 0.2348 | 0.4238 |
| $Children$ | 4.0250 | 1.7634 |
| $Father - None$ | 0.5321 | 0.4990 |
| $Father - Primary$ | 0.1485 | 0.3556 |
| $Father - Middle$ | 0.1289 | 0.3351 |
| $Father - High$ | 0.1333 | 0.3399 |
| $Father - College$ | 0.0572 | 0.2322 |
| $Mother - None$ | 0.7409 | 0.4381 |
| $Mother - Primary$ | 0.1052 | 0.3068 |
| $Mother - Middle$ | 0.0755 | 0.2643 |
| $Mother - High$ | 0.0587 | 0.2351 |
| $Mother - College$ | 0.0196 | 0.1386 |
| $WorkingMother$ | 0.3284 | 0.4696 |
| $LogExpenditure$ | 5.0487 | 0.5982 |
| $Asset$ | 0.6669 | 0.4713 |
| $Age$ | 9.3615 | 2.8263 |
| $Agesq$ | 95.6251 | 53.7571 |
| $Urban$ | 0.3427 | 0.4746 |
| $Lowcaste$ | 0.3529 | 0.4779 |
| $Muslim$ | 0.1505 | 0.3576 |
| $July - Sep$ | 0.2492 | 0.4325 |
| $Oct - Dec$ | 0.2523 | 0.4343 |
| $Jan - March$ | 0.2476 | 0.4316 |
| $April - June$ | 0.2509 | 0.4335 |
| $Male$ | 0.5287 | 0.4992 |

Source: NSSO Data, 1983, 1988, 1993, and 1999.

Per capita monthly household expenditure ($LogExpenditure$) is adjusted to 1988 Rupees.

Table 7: Probit Estimates for Participation in Full Time or Part Time Child Labor (Correcting Standard Errors for Clustering)

| **Variable** | All Children | Robust Standard Error | Interaction with Male Dummy | Robust Standard Error |
|---|---|---|---|---|
| $Rate-Primary$ | -0.0358 | 0.1081 | -0.4042 | 0.1723** |
| $Rate-Middle$ | -0.1014 | 0.0527* | 0.0498 | 0.0797 |
| $Year-88$ | 0.2824 | 0.0244*** | 0.0009 | 0.0158 |
| $Year-93$ | 0.2284 | 0.0248*** | 0.0020 | 0.0174 |
| $Year-99$ | 0.2021 | 0.0222*** | 0.0402 | 0.0166** |
| $Children$ | 0.0205 | 0.0037*** | 0.0036 | 0.0011*** |
| $Father-Primary$ | -0.1107 | 0.0058*** | 0.0074 | 0.0054 |
| $Father-Middle$ | -0.1420 | 0.0070*** | 0.0063 | 0.0062 |
| $Father-High$ | -0.1750 | 0.0085*** | 0.0252 | 0.0067*** |
| $Father-College$ | -0.1763 | 0.0097*** | 0.0067 | 0.0115 |
| $Mother-Primary$ | -0.0998 | 0.0061*** | 0.0703 | 0.0082*** |
| $Mother-Middle$ | -0.0908 | 0.0087*** | 0.0760 | 0.0099*** |
| $Mother-High$ | -0.0685 | 0.0150*** | 0.0866 | 0.0129*** |
| $Mother-College$ | -0.0476 | 0.0177** | 0.0948 | 0.0187*** |
| $WorkingMother$ | 0.0630 | 0.0070*** | -0.0225 | 0.0062*** |
| $LogExpenditure$ | -0.0784 | 0.0075*** | 0.0046 | 0.0053 |
| $Asset$ | -0.0070 | 0.0075 | -0.0155 | 0.0056*** |
| $Age$ | -0.1567 | 0.0151*** | -0.0302 | 0.0046*** |
| $Agesq$ | 0.0089 | 0.0005*** | 0.0006 | 0.0002*** |
| $Urban$ | -0.0797 | 0.0062*** | 0.0318 | 0.0062*** |
| $Lowcaste$ | 0.0514 | 0.0058*** | 0.0020 | 0.0046 |
| $Muslim$ | 0.0563 | 0.0108*** | 0.0034 | 0.0076 |
| $Oct-Dec$ | -0.0051 | 0.0059 | -0.0031 | 0.0052 |
| $Jan-March$ | -0.0204 | 0.0062*** | -0.0036 | 0.0051 |
| $April-June$ | 0.0005 | 0.0085 | 0.0039 | 0.0059 |
| $Male$ | 0.0800 | 0.0412* | | |
| | | | | |
| N | 440039 | | | |
| Predicted DV | 0.2476 | | | |
| Pseudo R-Square | 0.1836 | | | |

Marginal effects of independent variables and interactions of all independent variables with the male dummy are reported. Robust standard errors, corrected for clustering at the year-state level: *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 8: Probit Estimates for Participation in Full Time or Part Time Schooling (Correcting Standard Errors for Clustering)

| **Variable** | All Children | Robust Standard Error | Interaction with Male Dummy | Robust Standard Error |
|---|---|---|---|---|
| $Rate-Primary$ | -0.1031 | 0.1119 | 0.5693 | 0.1540*** |
| $Rate-Middle$ | 0.0174 | 0.0439 | 0.1168 | 0.0591** |
| $Year-88$ | 0.0491 | 0.0142*** | -0.0185 | 0.0225 |
| $Year-93$ | 0.1432 | 0.0135*** | -0.0077 | 0.0221 |
| $Year-99$ | 0.1903 | 0.0111*** | -0.0547 | 0.0208*** |
| $Children$ | 0.0010 | 0.0015 | -0.0010 | 0.0012 |
| $Father-Primary$ | 0.1480 | 0.0044*** | -0.0201 | 0.0048*** |
| $Father-Middle$ | 0.1856 | 0.0049*** | -0.0151 | 0.0061** |
| $Father-High$ | 0.2207 | 0.0070*** | -0.0221 | 0.0066*** |
| $Father-College$ | 0.2274 | 0.0075*** | -0.0168 | 0.0131 |
| $Mother-Primary$ | 0.1308 | 0.0057*** | -0.0737 | 0.0088 |
| $Mother-Middle$ | 0.1377 | 0.0067*** | -0.0894 | 0.0111 |
| $Mother-High$ | 0.1250 | 0.0097*** | -0.0812 | 0.0136 |
| $Mother-College$ | 0.1226 | 0.0162*** | -0.1180 | 0.0252 |
| $WorkingMother$ | -0.0788 | 0.0073*** | 0.0401 | 0.0076 |
| $LogExpenditure$ | 0.1277 | 0.0059*** | -0.0112 | 0.0062* |
| $Asset$ | 0.0113 | 0.007 | 0.0220 | 0.0057*** |
| $Age$ | 0.2619 | 0.0092*** | 0.0335 | 0.0046*** |
| $Agesq$ | -0.0135 | 0.0003*** | -0.0009 | 0.0002*** |
| $Urban$ | 0.1104 | 0.0086*** | -0.0517 | 0.0080*** |
| $Lowcaste$ | -0.0633 | 0.0062*** | -0.0066 | 0.0058 |
| $Muslim$ | -0.1041 | 0.0117*** | -0.0095 | 0.0092 |
| $Oct-Dec$ | -0.0100 | 0.0051* | -0.0041 | 0.0054 |
| $Jan-March$ | 0.0086 | 0.0052 | -0.0009 | 0.0048 |
| $April-June$ | -0.0395 | 0.0101*** | -0.0118 | 0.0062* |
| $Male$ | -0.0323 | 0.0432 | | |
| | | | | |
| N | 440039 | | | |
| Predicted DV | 0.7074 | | | |
| Pseudo R-Square | 0.2508 | | | |

Marginal effects of independent variables and interactions of all independent variables with the male dummy are reported. Robust standard errors, corrected for clustering at the year-state level: *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 9: Probit Estimates for Participation in Full Time or Part Time Child Labor (Without Correcting Standard Errors for Clustering)

| **Variable** | All Children | Standard Error | Interaction with Male Dummy | Standard Error |
|---|---|---|---|---|
| $Rate - Primary$ | -0.0358 | 0.0173** | -0.4042 | 0.0311*** |
| $Rate - Middle$ | -0.1014 | 0.0079*** | 0.0498 | 0.0131*** |
| $Year - 88$ | 0.2824 | 0.0032*** | 0.0009 | 0.0040 |
| $Year - 93$ | 0.2284 | 0.0036*** | 0.0020 | 0.0045 |
| $Year - 99$ | 0.2021 | 0.0037*** | 0.0402 | 0.0048*** |
| $Children$ | 0.0205 | 0.0005*** | 0.0036 | 0.0007*** |
| $Father - Primary$ | -0.1107 | 0.0023*** | 0.0074 | 0.0042* |
| $Father - Middle$ | -0.1420 | 0.0024*** | 0.0063 | 0.0049 |
| $Father - High$ | -0.1750 | 0.0025*** | 0.0252 | 0.0059*** |
| $Father - College$ | -0.1763 | 0.0035*** | 0.0067 | 0.0096 |
| $Mother - Primary$ | -0.0998 | 0.0030*** | 0.0703 | 0.0061*** |
| $Mother - Middle$ | -0.0908 | 0.0039*** | 0.0760 | 0.0078*** |
| $Mother - High$ | -0.0685 | 0.0053*** | 0.0866 | 0.0099*** |
| $Mother - College$ | -0.0476 | 0.0098*** | 0.0948 | 0.0178*** |
| $WorkingMother$ | 0.0630 | 0.0023*** | -0.0225 | 0.0029*** |
| $LogExpenditure$ | -0.0784 | 0.0021*** | 0.0046 | 0.0030 |
| $Asset$ | -0.0070 | 0.0025*** | -0.0155 | 0.0034*** |
| $Age$ | -0.1567 | 0.0026*** | -0.0302 | 0.0036*** |
| $Agesq$ | 0.0089 | 0.0001*** | 0.0006 | 0.0001*** |
| $Urban$ | -0.0797 | 0.0025*** | 0.0318 | 0.0039*** |
| $Lowcaste$ | 0.0514 | 0.0024*** | 0.0020 | 0.0032 |
| $Muslim$ | 0.0563 | 0.0032*** | 0.0034 | 0.0041 |
| $Oct - Dec$ | -0.0051 | 0.0027* | -0.0031 | 0.0038 |
| $Jan - March$ | -0.0204 | 0.0027*** | -0.0036 | 0.0039 |
| $April - June$ | 0.0005 | 0.0027 | 0.0039 | 0.0039 |
| $Male$ | 0.0800 | 0.0219*** | | |
| | | | | |
| N | 440039 | | | |
| Predicted DV | 0.2476 | | | |
| Pseudo R-Square | 0.1836 | | | |

Marginal effects of independent variables and interactions of all independent variables with the male dummy are reported. Standard errors, not corrected for clustering at the year-state level: *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 10: Probit Estimates for Participation in Full Time or Part Time Schooling (Without Correcting Standard Errors for Clustering)

| **Variable** | All Children | Standard Error | Interaction with Male Dummy | Standard Error |
|---|---|---|---|---|
| $Rate - Primary$ | -0.1031 | 0.0193*** | 0.5693 | 0.0343*** |
| $Rate - Middle$ | 0.0174 | 0.0089* | 0.1168 | 0.0143*** |
| $Year - 88$ | 0.0491 | 0.0029*** | -0.0185 | 0.0042*** |
| $Year - 93$ | 0.1432 | 0.0028*** | -0.0077 | 0.0047 |
| $Year - 99$ | 0.1903 | 0.0027*** | -0.0547 | 0.0051*** |
| $Children$ | 0.0010 | 0.0006 | -0.0010 | 0.0008 |
| $Father - Primary$ | 0.1480 | 0.0025*** | -0.0201 | 0.0046*** |
| $Father - Middle$ | 0.1856 | 0.0025*** | -0.0151 | 0.0054*** |
| $Father - High$ | 0.2207 | 0.0027*** | -0.0221 | 0.0064*** |
| $Father - College$ | 0.2274 | 0.0037*** | -0.0168 | 0.0114 |
| $Mother - Primary$ | 0.1308 | 0.0033*** | -0.0737 | 0.0065*** |
| $Mother - Middle$ | 0.1377 | 0.0042*** | -0.0894 | 0.0088*** |
| $Mother - High$ | 0.1250 | 0.0057*** | -0.0812 | 0.0116*** |
| $Mother - College$ | 0.1226 | 0.0108*** | -0.1180 | 0.0224*** |
| $WorkingMother$ | -0.0788 | 0.0025*** | 0.0401 | 0.0031*** |
| $LogExpenditure$ | 0.1277 | 0.0024*** | -0.0112 | 0.0033*** |
| $Asset$ | 0.0113 | 0.0028*** | 0.0220 | 0.0037*** |
| $Age$ | 0.2619 | 0.0029*** | 0.0335 | 0.0040*** |
| $Agesq$ | -0.0135 | 0.0001*** | -0.0009 | 0.0002*** |
| $Urban$ | 0.1104 | 0.0027*** | -0.0517 | 0.0042*** |
| $Lowcaste$ | -0.0633 | 0.0027*** | -0.0066 | 0.0036* |
| $Muslim$ | -0.1041 | 0.0036*** | -0.0095 | 0.0045** |
| $Oct - Dec$ | -0.0100 | 0.0031*** | -0.0041 | 0.0043 |
| $Jan - March$ | 0.0086 | 0.0031*** | -0.0009 | 0.0043 |
| $April - June$ | -0.0395 | 0.0031*** | -0.0118 | 0.0043*** |
| $Male$ | -0.0323 | 0.0250 | | |
| | | | | |
| N | 440039 | | | |
| Predicted DV | 0.7074 | | | |
| Pseudo R-Square | 0.2508 | | | |

Marginal effects of independent variables and interactions of all independent variables with the male dummy are reported. Standard errors, not corrected for clustering at the year-state level: *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 11: Probit Estimates for Participation in Full Time or Part Time Child Labor (Excluding Domestic Chores from Child Labor)

| **Variable** | All Children | Robust Standard Error | Interaction with Male Dummy | Robust Standard Error |
|---|---|---|---|---|
| $Rate-Primary$ | -0.0687 | 0.0875 | -0.2198 | 0.1528 |
| $Rate-Middle$ | -0.1108 | 0.0403*** | 0.0984 | 0.0652 |
| $Year-88$ | 0.3781 | 0.0277*** | -0.0733 | 0.0108*** |
| $Year-93$ | 0.3415 | 0.0276*** | -0.0740 | 0.0106*** |
| $Year-99$ | 0.3426 | 0.0275*** | -0.0644 | 0.0110*** |
| $Children$ | 0.0217 | 0.0032*** | -0.0002 | 0.0009 |
| $Father-Primary$ | -0.0834 | 0.0046*** | -0.0079 | 0.0044* |
| $Father-Middle$ | -0.1043 | 0.0057*** | -0.0142 | 0.0050*** |
| $Father-High$ | -0.1238 | 0.0076*** | -0.0115 | 0.0058* |
| $Father-College$ | -0.1208 | 0.0090*** | -0.0354 | 0.0088*** |
| $Mother-Primary$ | -0.0654 | 0.0055*** | 0.0291 | 0.0065*** |
| $Mother-Middle$ | -0.0542 | 0.0082*** | 0.0257 | 0.0074*** |
| $Mother-High$ | -0.0367 | 0.0132*** | 0.0387 | 0.0097*** |
| $Mother-College$ | -0.0257 | 0.0156 | 0.0514 | 0.0159*** |
| $WorkingMother$ | 0.0646 | 0.0084*** | -0.0289 | 0.0066*** |
| $LogExpenditure$ | -0.0603 | 0.0069*** | -0.0029 | 0.0052 |
| $Asset$ | -0.0004 | 0.0066 | -0.0217 | 0.0046*** |
| $Age$ | -0.1174 | 0.0090*** | -0.0528 | 0.0068*** |
| $Agesq$ | 0.0053 | 0.0003*** | 0.0034 | 0.0003*** |
| $Urban$ | -0.0537 | 0.0050*** | 0.0145 | 0.0048*** |
| $Lowcaste$ | 0.0437 | 0.0052*** | -0.0012 | 0.0041 |
| $Muslim$ | 0.0334 | 0.0106*** | 0.0149 | 0.0072** |
| $Oct-Dec$ | -0.0010 | 0.0062 | -0.0046 | 0.0052 |
| $Jan-March$ | -0.0076 | 0.0068 | -0.0101 | 0.0043** |
| $April-June$ | 0.0110 | 0.0075 | -0.0040 | 0.0047 |
| $Male$ | 0.2601 | 0.0387*** | | |
| | | | | |
| N | 440039 | | | |
| Predicted DV | 0.1965 | | | |
| Pseudo R-Square | 0.1796 | | | |

Marginal effects of independent variables and interactions of all independent variables with the male dummy are reported. Robust standard errors, corrected for clustering at the year-state level: *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 12: Probit Estimates for Participation in Full Time Child Labor

| **Variable** | All Children | Robust Standard Error | Interaction with Male Dummy | Robust Standard Error |
|---|---|---|---|---|
| $Rate - Primary$ | 0.0147 | 0.0840 | -0.2857 | 0.1419** |
| $Rate - Middle$ | -0.0488 | 0.0405 | -0.0193 | 0.0625 |
| $Year - 88$ | 0.2857 | 0.0203*** | -0.0013 | 0.0146 |
| $Year - 93$ | 0.1839 | 0.0234*** | -0.0040 | 0.0171 |
| $Year - 99$ | 0.1331 | 0.0198*** | 0.0312 | 0.0148** |
| $Children$ | -0.0006 | 0.0011 | 0.0009 | 0.0010 |
| $Father - Primary$ | -0.1003 | 0.0051*** | 0.0034 | 0.0047 |
| $Father - Middle$ | -0.1321 | 0.0060*** | 0.0024 | 0.0055 |
| $Father - High$ | -0.1606 | 0.0072*** | 0.0144 | 0.0060** |
| $Father - College$ | -0.1631 | 0.0081*** | 0.0112 | 0.0123 |
| $Mother - Primary$ | -0.1032 | 0.0042*** | 0.0639 | 0.0080*** |
| $Mother - Middle$ | -0.1117 | 0.0058*** | 0.0778 | 0.0108*** |
| $Mother - High$ | -0.1083 | 0.0080*** | 0.0880 | 0.0134*** |
| $Mother - College$ | -0.1074 | 0.0113*** | 0.1137 | 0.0236*** |
| $WorkingMother$ | 0.0564 | 0.0057*** | -0.0210 | 0.0057*** |
| $LogExpenditure$ | -0.0852 | 0.0071*** | -0.0018 | 0.0048 |
| $Asset$ | -0.0053 | 0.0064 | -0.0146 | 0.0053*** |
| $Age$ | -0.1527 | 0.0150*** | -0.0297 | 0.0042*** |
| $Agesq$ | 0.0087 | 0.0005*** | 0.0006 | 0.0002*** |
| $Urban$ | -0.0744 | 0.0055*** | 0.0298 | 0.0061*** |
| $Lowcaste$ | 0.0448 | 0.0057*** | 0.0044 | 0.0046 |
| $Muslim$ | 0.0745 | 0.0090*** | 0.0077 | 0.0068 |
| $Oct - Dec$ | 0.0129 | 0.0038*** | 0.0020 | 0.0049 |
| $Jan - March$ | 0.0029 | 0.0039 | 0.0027 | 0.0046 |
| $April - June$ | 0.0347 | 0.0083*** | 0.0122 | 0.0055** |
| $Male$ | 0.1157 | 0.0369*** | | |
| | | | | |
| N | 440039 | | | |
| Predicted DV | 0.2073 | | | |
| Pseudo R-Square | 0.2078 | | | |

Marginal effects of independent variables and interactions of all independent variables with the male dummy are reported. Robust standard errors, corrected for clustering at the year-state level: *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 13: Probit Estimates for Participation in Full Time Schooling

| **Variable** | All Children | Robust Standard Error | Interaction with Male Dummy | Robust Standard Error |
|---|---|---|---|---|
| $Rate-Primary$ | -0.0498 | 0.1408 | 0.7079 | 0.1893*** |
| $Rate-Middle$ | 0.0710 | 0.0607 | 0.0437 | 0.0787 |
| $Year-88$ | 0.0624 | 0.0224*** | -0.0246 | 0.0226 |
| $Year-93$ | 0.1123 | 0.0205*** | -0.0178 | 0.0217 |
| $Year-99$ | 0.1385 | 0.0222*** | -0.0666 | 0.0212*** |
| $Children$ | -0.0229 | 0.0044*** | -0.0025 | 0.0012** |
| $Father-Primary$ | 0.1551 | 0.0056*** | -0.0233 | 0.0051*** |
| $Father-Middle$ | 0.1908 | 0.0071*** | -0.0192 | 0.0065*** |
| $Father-High$ | 0.2300 | 0.0095*** | -0.0345 | 0.0069*** |
| $Father-College$ | 0.2356 | 0.0107*** | -0.0130 | 0.0121 |
| $Mother-Primary$ | 0.1220 | 0.0076*** | -0.0761 | 0.0089*** |
| $Mother-Middle$ | 0.1056 | 0.0104*** | -0.0814 | 0.0103*** |
| $Mother-High$ | 0.0684 | 0.0175*** | -0.0784 | 0.0130*** |
| $Mother-College$ | 0.0362 | 0.0224 | -0.0895 | 0.0198*** |
| $WorkingMother$ | -0.0791 | 0.0086*** | 0.0380 | 0.0079*** |
| $LogExpenditure$ | 0.1120 | 0.0080*** | -0.0148 | 0.0063** |
| $Asset$ | 0.0104 | 0.0084 | 0.0216 | 0.0061*** |
| $Age$ | 0.2548 | 0.0096*** | 0.0329 | 0.0048*** |
| $Agesq$ | -0.0131 | 0.0004*** | -0.0009 | 0.0002*** |
| $Urban$ | 0.1104 | 0.0095*** | -0.0494 | 0.0080*** |
| $Lowcaste$ | -0.0661 | 0.0069*** | -0.0046 | 0.0058 |
| $Muslim$ | -0.0795 | 0.0143*** | -0.0055 | 0.0097 |
| $Oct-Dec$ | 0.0106 | 0.0073 | 0.0004 | 0.0059 |
| $Jan-March$ | 0.0350 | 0.0072*** | 0.0041 | 0.0053 |
| $April-June$ | 0.0012 | 0.0100 | -0.0058 | 0.0064 |
| $Male$ | -0.0074 | 0.0431 | | |
| | | | | |
| N | 440039 | | | |
| Predicted DV | 0.6641 | | | |
| Pseudo R-Square | 0.2097 | | | |

Marginal effects of independent variables and interactions of all independent variables with the male dummy are reported. Robust standard errors, corrected for clustering at the year-state level: *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 14: Probit Estimates for Participation in Part Time Child Labor & Schooling

| **Variable** | All Children | Robust Standard Error | Interaction with Male Dummy | Robust Standard Error |
|---|---|---|---|---|
| $Rate - Primary$ | -0.0011 | 0.0008 | -0.0011 | 0.0013 |
| $Rate - Middle$ | -0.0011 | 0.0004*** | 0.0013 | 0.0008* |
| $Year - 88$ | -0.0001 | 0.0003 | -0.0002 | 0.0002 |
| $Year - 93$ | 0.0455 | 0.0145*** | -0.0004 | 0.0001** |
| $Year - 99$ | 0.0626 | 0.0163*** | -0.0004 | 0.0001** |
| $Children$ | 0.0004 | 0.0001*** | 0.0000 | 0.0000 |
| $Father - Primary$ | 0.0003 | 0.0001*** | -0.0001 | 0.0000 |
| $Father - Middle$ | 0.0004 | 0.0001*** | -0.0001 | 0.0000*** |
| $Father - High$ | 0.0002 | 0.0001*** | 0.0000 | 0.0000 |
| $Father - College$ | 0.0002 | 0.0001*** | -0.0002 | 0.0000** |
| $Mother - Primary$ | 0.0004 | 0.0001*** | -0.0001 | 0.0000*** |
| $Mother - Middle$ | 0.0005 | 0.0001*** | -0.0001 | 0.0000** |
| $Mother - High$ | 0.0008 | 0.0002*** | -0.0001 | 0.0000 |
| $Mother - College$ | 0.0013 | 0.0004*** | -0.0001 | 0.0000 |
| $WorkingMother$ | 0.0000 | 0.0000 | 0.0001 | 0.0000 |
| $LogExpenditure$ | 0.0004 | 0.0001*** | 0.0000 | 0.0000 |
| $Asset$ | -0.0001 | 0.0000* | 0.0000 | 0.0000 |
| $Age$ | 0.0002 | 0.0000*** | -0.0001 | 0.0000** |
| $Agesq$ | 0.0000 | 0.0000*** | 0.0000 | 0.0000** |
| $Urban$ | -0.0001 | 0.0000 | 0.0000 | 0.0000 |
| $Lowcaste$ | 0.0001 | 0.0000 | -0.0001 | 0.0000*** |
| $Muslim$ | -0.0004 | 0.0001*** | 0.0000 | 0.0000 |
| $Oct - Dec$ | -0.0004 | 0.0001*** | 0.0000 | 0.0000 |
| $Jan - March$ | -0.0005 | 0.0001*** | 0.0000 | 0.0000 |
| $April - June$ | -0.0007 | 0.0001*** | 0.0000 | 0.0000 |
| $Male$ | 0.0017 | 0.0011** | | |
| | | | | |
| N | 439706 | | | |
| Predicted DV | 0.0003 | | | |
| Pseudo R-Square | 0.4518 | | | |

Marginal effects of independent variables and interactions of all independent variables with the male dummy are reported. Robust standard errors, corrected for clustering at the year-state level: *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 15: Probit Estimates for Participation in Full Time or Part Time Child Labor - Excluding $LogExpenditure$

| **Variable** | All Children | Robust Standard Error | Interaction with Male Dummy | Robust Standard Error |
|---|---|---|---|---|
| $Rate - Primary$ | -0.0402 | 0.1078 | -0.4080 | 0.1724** |
| $Rate - Middle$ | -0.1021 | 0.0527* | 0.0548 | 0.0794 |
| $Year - 88$ | 0.2592 | 0.0240*** | 0.0026 | 0.0158 |
| $Year - 93$ | 0.1987 | 0.0242*** | 0.0035 | 0.0171 |
| $Year - 99$ | 0.1572 | 0.0221*** | 0.0412 | 0.0166** |
| $Children$ | 0.0237 | 0.0037*** | 0.0035 | 0.0010*** |
| $Father - Primary$ | -0.1173 | 0.0059*** | 0.0078 | 0.0053 |
| $Father - Middle$ | -0.1510 | 0.0072*** | 0.0070 | 0.0062 |
| $Father - High$ | -0.1883 | 0.0086*** | 0.0262 | 0.0064*** |
| $Father - College$ | -0.1922 | 0.0093*** | 0.0080 | 0.0109 |
| $Mother - Primary$ | -0.1057 | 0.0062*** | 0.0709 | 0.0082*** |
| $Mother - Middle$ | -0.1001 | 0.0088*** | 0.0774 | 0.0098*** |
| $Mother - High$ | -0.0868 | 0.0144*** | 0.0884 | 0.0125*** |
| $Mother - College$ | -0.0840 | 0.0162*** | 0.0975 | 0.0179*** |
| $WorkingMother$ | 0.0689 | 0.0070*** | -0.0227 | 0.0061*** |
| $Asset$ | -0.0135 | 0.0074* | -0.0141 | 0.0057** |
| $Age$ | -0.1566 | 0.0150*** | -0.0304 | 0.0046*** |
| $Agesq$ | 0.0089 | 0.0005*** | 0.0006 | 0.0002*** |
| $Urban$ | -0.0914 | 0.0060*** | 0.0327 | 0.0061*** |
| $Lowcaste$ | 0.0614 | 0.0064*** | 0.0020 | 0.0047 |
| $Muslim$ | 0.0587 | 0.0109*** | 0.0036 | 0.0076 |
| $Oct - Dec$ | -0.0055 | 0.0061 | -0.0036 | 0.0052 |
| $Jan - March$ | -0.0212 | 0.0062*** | -0.0038 | 0.0051 |
| $April - June$ | -0.0013 | 0.0084 | 0.0038 | 0.0058 |
| $Male$ | 0.1005 | 0.0266*** | | |
| | | | | |
| N | 440039 | | | |
| Predicted DV | 0.2488 | | | |
| Pseudo R-Square | 0.1790 | | | |

Marginal effects of independent variables and interactions of all independent variables with the male dummy are reported. Robust standard errors, corrected for clustering at the year-state level: *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 16: Probit Estimates for Participation in Full Time or Part Time Schooling - Excluding $LogExpenditure$

| **Variable** | All Children | Robust Standard Error | Interaction with Male Dummy | Robust Standard Error |
|---|---|---|---|---|
| $Rate - Primary$ | -0.0937 | 0.1113 | 0.5789 | 0.1561*** |
| $Rate - Middle$ | 0.0195 | 0.0439 | 0.1085 | 0.0596* |
| $Year - 88$ | 0.0775 | 0.0138*** | -0.0217 | 0.0225 |
| $Year - 93$ | 0.1742 | 0.0124*** | -0.0105 | 0.0219 |
| $Year - 99$ | 0.2352 | 0.0101*** | -0.0568 | 0.0212*** |
| $Children$ | -0.0043 | 0.0015*** | -0.0008 | 0.0011 |
| $Father - Primary$ | 0.1579 | 0.0044*** | -0.0208 | 0.0046*** |
| $Father - Middle$ | 0.1991 | 0.0049*** | -0.0166 | 0.0058*** |
| $Father - High$ | 0.2407 | 0.0067*** | -0.0245 | 0.0063*** |
| $Father - College$ | 0.2489 | 0.0065*** | -0.0193 | 0.0122 |
| $Mother - Primary$ | 0.1401 | 0.0057*** | -0.0752 | 0.0088*** |
| $Mother - Middle$ | 0.1513 | 0.0066*** | -0.0912 | 0.0109*** |
| $Mother - High$ | 0.1507 | 0.0089*** | -0.0850 | 0.0133*** |
| $Mother - College$ | 0.1694 | 0.0128*** | -0.1219 | 0.0241*** |
| $WorkingMother$ | -0.0876 | 0.0073*** | 0.0403 | 0.0074*** |
| $Asset$ | 0.0213 | 0.0071*** | 0.0197 | 0.0057*** |
| $Age$ | 0.2601 | 0.0091*** | 0.0341 | 0.0045*** |
| $Agesq$ | -0.0133 | 0.0003*** | -0.0009 | 0.0002*** |
| $Urban$ | 0.1276 | 0.0081*** | -0.0532 | 0.0081*** |
| $Lowcaste$ | -0.0789 | 0.0067*** | -0.0070 | 0.0058 |
| $Muslim$ | -0.1067 | 0.0116*** | -0.0100 | 0.0092 |
| $Oct - Dec$ | -0.0090 | 0.0052* | -0.0034 | 0.0054 |
| $Jan - March$ | 0.0104 | 0.0053* | -0.0007 | 0.0048 |
| $April - June$ | -0.0354 | 0.0101*** | -0.0119 | 0.0061 |
| $Male$ | -0.0847 | 0.0247*** | | |
| | | | | |
| N | 440039 | | | |
| Predicted DV | 0.7054 | | | |
| Pseudo R-Square | 0.2416 | | | |

Marginal effects of independent variables and interactions of all independent variables with the male dummy are reported. Robust standard errors, corrected for clustering at the year-state level: *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 17: Probit Estimates for Participation in Full Time or Part Time Child Labor - Including Rates of Return to High School & College

| **Variable** | All Children | Robust Standard Error | Interaction with Male Dummy | Robust Standard Error |
|---|---|---|---|---|
| $Rate - Primary$ | -0.0145 | 0.1071 | -0.5241 | 0.2092** |
| $Rate - Middle$ | -0.0861 | 0.0528 | 0.0475 | 0.0818 |
| $Rate - High$ | 0.0342 | 0.0367 | 0.1215 | 0.1282 |
| $Rate - College$ | 0.0244 | 0.0358 | 0.1217 | 0.0964 |
| $Year - 88$ | 0.2812 | 0.0242*** | 0.0054 | 0.0163 |
| $Year - 93$ | 0.2300 | 0.0245*** | -0.0082 | 0.0185 |
| $Year - 99$ | 0.2000 | 0.0221*** | 0.0295 | 0.0189 |
| $Children$ | 0.0203 | 0.0037*** | 0.0038 | 0.0011*** |
| $Father - Primary$ | -0.1110 | 0.0057*** | 0.0081 | 0.0054 |
| $Father - Middle$ | -0.1423 | 0.0069*** | 0.0070 | 0.0061 |
| $Father - High$ | -0.1751 | 0.0085*** | 0.0251 | 0.0065*** |
| $Father - College$ | -0.1763 | 0.0097*** | 0.0064 | 0.0112 |
| $Mother - Primary$ | -0.1002 | 0.0061*** | 0.0714 | 0.0083*** |
| $Mother - Middle$ | -0.0915 | 0.0086*** | 0.0771 | 0.0100*** |
| $Mother - High$ | -0.0691 | 0.0150*** | 0.0875 | 0.0128*** |
| $Mother - College$ | -0.0482 | 0.0176** | 0.0957 | 0.0186*** |
| $WorkingMother$ | 0.0636 | 0.0070*** | -0.0240 | 0.0064*** |
| $LogExpenditure$ | -0.0783 | 0.0075*** | 0.0048 | 0.0053 |
| $Asset$ | -0.0079 | 0.0075 | -0.0143 | 0.0056** |
| $Age$ | -0.1566 | 0.0151*** | -0.0302 | 0.0047*** |
| $Agesq$ | 0.0089 | 0.0005*** | 0.0006 | 0.0002*** |
| $Urban$ | -0.0793 | 0.0062*** | 0.0308 | 0.0064*** |
| $Lowcaste$ | 0.0505 | 0.0058*** | 0.0036 | 0.0048 |
| $Muslim$ | 0.0560 | 0.0110*** | 0.0035 | 0.0079 |
| $Oct - Dec$ | -0.0051 | 0.0059 | -0.0029 | 0.0051 |
| $Jan - March$ | -0.0204 | 0.0062*** | -0.0034 | 0.0049 |
| $April - June$ | 0.0004 | 0.0085 | 0.0044 | 0.0058 |
| $Male$ | 0.0589 | 0.0439 | | |
| | | | | |
| N | 440039 | | | |
| Predicted DV | 0.2475 | | | |
| Pseudo R-Square | 0.1839 | | | |

Marginal effects of independent variables and interactions of all independent variables with the male dummy are reported. Robust standard errors, corrected for clustering at the year-state level: *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 18: Probit Estimates for Participation in Full Time or Part Time Schooling - Including Rates of Return to High School & College

| **Variable** | All Children | Robust Standard Error | Interaction with Male Dummy | Robust Standard Error |
|---|---|---|---|---|
| $Rate - Primary$ | -0.0755 | 0.1175 | 0.5590 | 0.1664*** |
| $Rate - Middle$ | 0.0300 | 0.0450 | 0.1118 | 0.0651* |
| $Rate - High$ | 0.0307 | 0.0280 | -0.0592 | 0.0773 |
| $Rate - College$ | 0.0184 | 0.0288 | -0.0193 | 0.0613 |
| $Year - 88$ | 0.0479 | 0.0147*** | -0.0177 | 0.0228 |
| $Year - 93$ | 0.1442 | 0.0121*** | -0.0072 | 0.0194 |
| $Year - 99$ | 0.1884 | 0.0113*** | -0.0508 | 0.0218** |
| $Children$ | 0.0009 | 0.0015 | -0.0010 | 0.0012 |
| $Father - Primary$ | 0.1477 | 0.0044*** | -0.0196 | 0.0048*** |
| $Father - Middle$ | 0.1854 | 0.0049*** | -0.0147 | 0.0060** |
| $Father - High$ | 0.2206 | 0.0069*** | -0.0217 | 0.0066*** |
| $Father - College$ | 0.2273 | 0.0075*** | -0.0163 | 0.0132 |
| $Mother - Primary$ | 0.1306 | 0.0057*** | -0.0733 | 0.0088*** |
| $Mother - Middle$ | 0.1376 | 0.0068*** | -0.0889 | 0.0110*** |
| $Mother - High$ | 0.1247 | 0.0097*** | -0.0806 | 0.0134*** |
| $Mother - College$ | 0.1222 | 0.0162*** | -0.1171 | 0.0252*** |
| $WorkingMother$ | -0.0786 | 0.0073*** | 0.0397 | 0.0076*** |
| $LogExpenditure$ | 0.1285 | 0.0059*** | -0.0127 | 0.0061** |
| $Asset$ | 0.0114 | 0.0069* | 0.0218 | 0.0054*** |
| $Age$ | 0.2619 | 0.0092*** | 0.0334 | 0.0046*** |
| $Agesq$ | -0.0135 | 0.0003*** | -0.0009 | 0.0002*** |
| $Urban$ | 0.1105 | 0.0086*** | -0.0521 | 0.0081*** |
| $Lowcaste$ | -0.0630 | 0.0063*** | -0.0073 | 0.0059 |
| $Muslim$ | -0.1048 | 0.0118*** | -0.0084 | 0.0092 |
| $Oct - Dec$ | -0.0101 | 0.0052* | -0.0039 | 0.0054 |
| $Jan - March$ | 0.0086 | 0.0052 | -0.0008 | 0.0047 |
| $April - June$ | -0.0397 | 0.0101*** | -0.0116 | 0.0061* |
| $Male$ | -0.0159 | 0.0451 | | |
| | | | | |
| N | 440039 | | | |
| Predicted DV | 0.7075 | | | |
| Pseudo R-Square | 0.2509 | | | |

Marginal effects of independent variables and interactions of all independent variables with the male dummy are reported. Robust standard errors, corrected for clustering at the year-state level: *Significant at 10%, **Significant at 5%, ***Significant at 1%.