The Role of Social Norms in Child Labor and Schooling in India

Rubiana Chamarbagwala*
Department of Economics
Indiana University - Bloomington

Rusty Tchernis
Department of Economics
Indiana University - Bloomington

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Abstract

This paper aims to summarize the unexplained propensity of children to engage in work, school, or neither. After controlling for a wide range of determinants of child labor, schooling, and idleness, we estimate a hierarchical model that allows for heteroskedastic, spatially correlated random effects. We use the posterior distribution of ranks of random effects to capture social norms toward children's activities in each district and thus identify those Indian districts where social attitudes favor education and oppose child labor and idleness. We propose that government intervention be targeted at districts with pro-schooling, anti-child-labor, and anti-idleness social attitudes if limited government resources necessitate implementing minimal cost policies that have the greatest potential to succeed.
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*Corresponding Author: Rubiana Chamarbagwala, Address: Department of Economics, Wylie Hall Room 105, 100 S. Woodlawn, Indiana University, Bloomington, IN 47405, Phone: 812-855-3996, Fax: 812-855-3736, E-mail: rchamarb@indiana.edu.

I INTRODUCTION

Not only is education critical to generating and sustaining economic development, it constitutes a basic human right of every child (United Nations 1948). Despite this, according to the 1991 census of India, more than 94 million Indian children are not attending school.[1] Many authors have examined why parents choose to educate their children or send them to work. In most cases economic factors are found to play an important role. Basu & Van (1998), Basu (2002), Ranjan (1999), for example, observe that poverty and credit constraints prevent households from undertaking potentially profitable investment in human capital as either schooling expenses are too high or child labor is necessary for survival of the household. Other authors look at the local labor market (Duryea & Arends-Kuening 2002, Krueger 2002), trade (Edmonds & Pavcnik 2004, Cigno et al. 2002), or economic growth (Barros et al. 1994, Neri & Thomas 2001, Swaminathan 1998). While constraints may prevent children from going to school, a low return to human capital due to relatively low wages for educated workers (Foster & Rosenzweig 1996, 2004, Kochar 2004) or a high probability of unemployment (Da Silva Leme & Wajnman 2000) may discourage children from going to school. Such children will not necessarily enter the labor market immediately but remain idle until they are old enough to work.

In this paper, we focus on a non-economic determinant of children's activities – namely, social norms. Social norms can play a crucial part even in economic decision making as individuals rarely choose their actions in isolation but embedded within their

[1]In the 5-14 age-group, 94,893,589 children don't attend school full time or part time. Of these 43,405,608 are boys and 51,487,981 are girls. These constitute 49% of all children, 43% of boys, and 55% of girls. Education data for children from the 2001 census has not yet been released.

social context. This has two consequences. First, society's acceptance or rejection of certain activities or behavior directly affects their (possibly psychological) cost and benefits. A social stigma attached to child labor might thus reduce the willingness of households to send their children to work. Moreover, through interaction with a normative environment, individuals may change their own attitudes, perceptions, and preferences and – unless their actual behavior is determined by binding constraints – this may influence their actions.

Previous theoretical and empirical research on the social determinants of children's activities is limited. Lopez-Calva & Miyamoto (2004) develop a theoretical model that shows how different social norms of filial obligations in more and less developed countries result in higher child labor and lower schooling in LDCs. Lopez-Calva (2003) shows how social norms affect child labor and schooling decisions through a cost associated with the stigma of not sending one's children to school. The author then tests the impact of norms in child schooling and labor outcomes in Mexico and finds that community variables have a significant effect on individual behavior. In particular, a higher school enrollment ratio within a community makes a child more likely to attend school while a high prevalence of child labor puts a child at a higher risk of working, too.

Regressing individual schooling outcomes on community schooling averages, is problematic for several reasons (Manski 1993). First, if a child is affected by her neighbors, then her neighbors are also affected by her, making community-level work and school endogenous and biasing regression result as a consequence. Moreover, omitted community variables such as returns to human capital or the effectiveness of local schools in human capital accumulation will most likely affect all children in a community equally and potentially introduce a spurious correlation between individuals' actions. Finally, the link between correlation and causation is not entirely clear. Parents may change their behavior based on local social norms, in which case community-level schooling affects their decision to send their children to school. Alternatively, parents may chose their community based on their own preferences, leading to high-schooling and low-schooling clusters without direct normative links.[2] However, while school quality and availability influence residential location choice in developed countries, this is not common in poorer countries like India. Migration from rural to rural areas is mostly due to marriage (for women) whereas rural to urban migration is driven by the availability of better employment opportunities for adults.

This paper attempts to link social norms to observable spatial dependence of children's activities in India. Spatial dependence or spatial correlation exists when a variable exhibits a systematic pattern rather than a random assignment across space. In other words, a value observed at a location depends on the values observed at neighboring locations. We estimate a hierarchical model where social norms operate and potentially influence parental decisions regarding school, work, and idleness for their children. We assume that there is a village- or urban-block-level random effect, where all households within the same village or urban block share common social attitudes or norms towards school, work, and idleness. We allow for heteroskedasticity of village- or urban-block-level random effects within a district. We also assume that there are spatially correlated unobservables among adjacent districts so that neighboring districts share similar social attitudes towards children's activities. Our hierarchical model avoids the econometric problems discussed above while allowing us to incorporate spatial correlation in chil-

[2] These empirical issues are addressed to some extent in the empirical literature on social interactions (Brock & Durlauf 2000, Glaeser et al. 1996, Gavaria 1997, Topa 1997) that focuses on economic actions such as crime, labor force participation, education choice, and out-of-wedlock births.

dren's activities.[3] Even though we model spatial correlation between districts rather than between villages, we acknowledge that the latter is preferable. However, while our data allows us to identify the villages and urban blocks that each district consists of, it does not provide the names of villages or urban blocks. Thus, data limitations prevent us from modeling spatial correlation at the village-level. Nevertheless, if spatial correlation exists at the village level, it should also exist at more aggregate levels. We thus model spatial correlation at the district-level, which our data allows us to do.

The use of spatial methods in estimating reduced form child labor and schooling decision models can provide additional information on household decision making that has so far not been treated adequately. School enrollment, child labor, and idleness (neither attending school nor working) are each examined separately in order to measure the social inclination towards each of these activities. We calculate the posterior distribution of ranks of district-level random effects, which measures the social propensity of households in a district towards education, child labor, and idleness. Each district-level random effect borrows information not only from the village-level random effects within that district but also from the random effects of its neighboring districts, which in turn borrow information from their respective villages and adjacent neighbors. Thus, our measure of each district's *social propensity* towards an activity captures the unexplained propensity at the *village-level* not only among all villages in that district but also among its neighboring districts' villages, its neighbors' neighbor's villages, and so on throughout the entire country.

Our results allow us to identify two groups of districts – one where government in-

[3]The entire country consists of 35 states and union territories, which in turn consists of districts. Each district comprises several villages and urban blocks.

terventions to promote schooling, such as building new schools or providing education subsidies, will have the greatest potential to succeed; the other where government intervention to reduce the prevalence of child labor, such as paying poor parents to send their children to school rather than to work, will be most effective. The first group of districts have both a high social propensity towards schooling and a low social propensity towards idleness for children. In the second group of districts, parents have a low social propensity towards sending their children to work. According to our analysis, these districts embody social attitudes that are favorable to schooling and oppose idleness and child labor. Thus, given adequate resources to educate one's children, parents in these districts will be most likely to seize opportunities to invest in their children's human capital.

The following section briefly describes the data. Section III formalizes the empirical model and discusses the empirical methodology. Results are presented in section IV and section V concludes with policy implications.

II DATA

Our data come from 4 sources. The majority of our data consist of household-level variables which come from the 55th Round of the Employment and Unemployment Schedule of the National Sample Survey Organization (NSSO) for the year 1999-2000. These variables include household-level socio-economic determinants of schooling, child labor, and idleness – i.e. household composition, parental education, caste, religion, per capita expenditure, land ownership, sector of residence, and season indicators. Using this data, we also calculate district-level measures of returns to education – i.e. the average wage for different education groups within a district.[4] Our second data source is the 55th Round of the Consumer Expenditure Schedule of the NSSO, from which calculate district level poverty measures – the head count ratio – which is a measure of absolute poverty in a district. The Census of India, 1991, provides information on public good provision for Indian villages. From this we calculate the proportion of villages within a district that have access to a primary, middle, and high school. Finally, state level data on the quality of schooling – i.e. the teacher-pupil ratio – in 1997-1998 is obtained from Selected Educational Statistics, published by the Department of Education in India.

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. Our sample includes children aged 5 to 14 years to adhere to the ILO's definition of child labor. Our data allows us to identify 6 distinct groups of children. Of these, 3 groups consist of children engaged in a single activity full time – i.e. school, work, and neither school nor work (idleness). The remaining 3 groups consist of children engaged in 2 part time activities – i.e. school and work, school and idleness, and work and idleness. Since the latter 3 groups are extremely small, we focus on the first 3 groups of children and estimate regressions for full time school, child labor, and idleness separately. The NSSO data reports the principal and subsidiary activities of all individuals during each day of the week prior to the survey. Rather than report the hours spent in each activity, two levels of intensity are reported - either full or half intensity per day. We identify children

[4]In order to estimate our regressions we use data for 28 states and union territories, which includes 71 regions and 408 districts. Each region consists of a group of contiguous districts that share similar cropping patterns and population density. Because we estimate spatial regressions we have to exclude districts that have no adjacent neighbors.

who attend school (work or remain idle) full time as those who report attending school (working or being idle) with full intensity for all seven days of the past week.[5]

Children who attend an educational institution are defined as attending school. We include as child laborers all children working in the market, a household enterprise, or those engaged in domestic duties. We include children engaged in domestic duties as child laborers because domestic duties constitute 'work' rather than 'leisure' since domestic work includes mostly cooking, cleaning, and taking care of younger siblings. While market and household enterprise work is performed mostly by boys, girls perform the majority of domestic chores in Indian households. We extend the standard conceptual framework to include the possibility of children who neither work nor attend school but instead remain idle.

Commonly referred to as 'nowhere' children, idle children have been excluded from most empirical research even though they constitute a larger proportion than working children. The exception is Deb & Rosati (2004), who find that unobserved heterogeneity at the household-level dominates observed income and wealth heterogeneity in determining child labor, schooling, and idleness among children in Ghana and India. We include idle children in our analysis not only because they constitute a large group in India but also because they could include children who work. This group consists both of children who are idle because they are looking for work and of those who don't need to work for economic reasons. The latter group consists of children whose parents either cannot afford to educate them – tuition and school supplies may be too expensive, or

[5]Even though all children attend school during five or at most six days of the week, these children report full intensity of attending school on seven days because they spend their free time engaged in homework or other school-related activities rather than in work or idleness. Defining participation in full time school as those who report attending school with full intensity for five or more days (or six or more days) of the past week does not change our regression results significantly.

education may be too inconvenient due to the scarcity or distance of schools – and those whose parents see no economic nor non-economic benefit from educating them. These children may also include those who work in the market or in a household enterprise and whose parents report them as idle simply to avoid reporting them as child laborers. However, such under-reporting of child labor and over-reporting of idleness is more likely in regions where parents are aware that child labor is illegal - i.e. in more developed and urban regions. Nowhere children may also include those engaged in domestic chores, who are mostly girls who perform household chores like cooking, cleaning, and caring for younger siblings, even though domestic chores should be considered work rather than idleness since these tasks constitute economically productive activities. Because idle children also consist of those who don't need to work for economic reasons, these children may be considerably different from those who attend school as well as those who work. Ignoring the difference may lead to unintended consequences of education policies. For example, if school is incorrectly thought of as the only alternative to work, a policy that reduces child work (via a ban on child labor) may simply increase the pool of idle children rather than increasing school attendance, especially if schooling costs are high or returns to schooling are low.

Table 1 shows the proportion of Indian children, boys, and girls engaged in each of the 6 groups in 1999-2000. Children who only attend school constitute the largest group (68%), followed closely by idle children (20%), while the proportion of children engaged in only work is small (5%). Several points are worth mentioning here. First, even though working children constitute a relatively small group, under-reporting of child labor may result in many child workers being included as idle children, making this latter group even more important to study. Second, significant gender disparities with respect to work, school, and idleness exist in India, with a greater share of boys attending school than girls (approximately 71% of boys versus 64% of girls). The proportion of boys engaged in work (3%) is less than girls (7%) since we include domestic chores as work. Moreover, idle girls constitute a larger group than idle boys (about 22% of girls versus 18% of boys). Not only are there large inter-state differences in the proportion of children who attend school, work, and remain idle, but also gender disparities are worse in some states than in others, as shown in Table 2.

III EMPIRICAL METHODOLOGY

We estimate three separate equations for children's participation in work, school, and neither work nor school. Because our outcomes are binary, we estimate binary probit models. The probit model assumes that there is a latent variable y^*_{hvd} that can be expressed as a linear function of variables that affect the probability of participation in work, school, and idleness. Each household h, residing in village or urban-block v, which is located in district d, has some utility, y^*_{hvd}, from sending its children to school, work, or neither school nor work. Besides observable characteristics, X_{hvd}, that are correlated with y^*_{hvd}, we assume that there is a village-level random effect δ_{vd} which captures the social propensity towards child labor, schooling, or idleness at the village-level. The village-level random effect δ_{vd} is normally distributed with mean γ_d and variance σ^2_d. These two parameters capture the mean and variance of village-level attitudes towards children's activities within district d. We also assume that all districts j in the neighborhood of district d, R_d, are correlated, where R_d consists of all districts adjacent to district d.

We estimate the following hierarchical model with 3 levels:

$$y^*_{hvd} = X_{hvd}\beta + \delta_{vd} + \epsilon_{hvd}, \epsilon_{hvd} \sim N(0,1) \quad (1)$$

$$\delta_{vd} = \gamma_d + u_{vd}, u_{vd} \sim N(0, \sigma_d^2) \quad (2)$$

$$\gamma_d | \gamma_{j,j \in R_d} = \sum_{j \in R_d} \omega\gamma_j + e_d, e_d \sim N(0, \tau^2) \quad (3)$$

where $h = 1, \ldots, H$ indexes households, $v = 1, \ldots, V$ indexes villages, and $d = 1, \ldots, D$ represents districts.

We use non-informative conjugate priors and estimate the model using Metropolis within Gibbs sampler with data augmentation (e.g. Chib (2001), Hogan & Tchernis (2004)).[6] The first level of the hierarchical model (Equation (1)) describes the relationship between the latent utility from work (school or idleness) y^*_{hvd}, observable characteristics X_{hvd}, and a village-level random effect δ_{vd}. The second level (Equation (2)) summarizes the distribution of village-level random effects or social norms towards children's activities, allowing for heteroskedasticity of these effects. The third level of the model (Equation (3)) describes the spatial dependence between the district-level random effects, γ_d, among adjacent districts. The degree of spatial dependency between adjacent districts is captured by ω while τ measures the remaining variability. The measure of spatial dependency ω is restricted to be between the reciprocals of the largest and smallest eigenvalues of the neighborhood weight matrix. Higher vales of τ represent less spatial dependence, meaning that conditional on a district's neighbor's values of γ there is still a lot of variability in the distribution of γ_d.

The specification in Equation (3) is known as a conditionally autoregressive model and results in a marginal distribution of $\gamma \sim N(0, B)$, where $B = (I_D - \omega W)T$ (Besag

[6]The sampling algorithm is available from the authors upon request.

1974), where W is the weight matrix with elements i, j equal to 1 for adjacent districts i and j, and $T = diag(\tau^2)$. Although our specification only shows a dstrict's dependence on it's adjacent neighbors, the marginal representation shows that all the districts in the country are correlated. [7] Hence, the posterior distribution of γ_d borrows information from two sources: the village level effects from the villages in the district as well as the district level effects of all other districts in the country.

The latent variable y^*_{hvd} is unobservable and instead a dummy variable is defined as $y_{hvd} = 1$ if one or more child aged 5 to 14 years in household h worked, attended school, or neither worked nor attended school during the past 7 days and zero otherwise:

$$y_{hvd} = \begin{cases} 1 & \text{if } y^*_{hvd} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The probit model assumes that the error term in Equation (1), ϵ_{hvd}, is distributed according to the standard normal distribution function. Therefore, the probability of one or more child in household h participating in work, school, or neither work nor school P_{hvd}, can be written as:

$$P_{hvd} = \text{pr}(y_{hvd} = 1) \tag{5a}$$

$$= \text{pr}(X_{hvd}\beta + \delta_{vd} + \epsilon_{hvd} > 0) \tag{5b}$$

$$= \text{pr}(\epsilon_{hvd} > -X_{hvd}\beta - \delta_{vd}) \tag{5c}$$

$$= \frac{1}{\sqrt{2\Pi}} \int_{-\infty}^{X_{hvd}\beta+\delta_{vd}} e^{-0.5t^2} dt \tag{5d}$$

where t is a standardized normal variable.

[7] A district's social norms are correlated with it's adjacent neighbors' social norms, it's neighbors' neighbors social norms, and so on throughout the entire country.

The explanatory variables included in X_{hvd} and described in Table 3 include household-, district-, and state-level controls. Household-level controls include the number of boys and girls in the household, four dummies each to capture the father's and mother's education levels,[8] the natural log of per capita household expenditure, a dummy that indicates if the household owns more than one acre of land, dummies that indicate whether or not the household belongs to a low caste (i.e. scheduled caste, scheduled tribe, or other backward caste) or Muslim religion, a dummy that indicates if the household lives in an urban area, and three season dummies to capture when the household was surveyed (July to September is the omitted season). Because district-level income levels and returns to schooling could influence parental decisions on whether or not to educate their children, we include a district-level measure of poverty (the head count ratio)[9] and returns to schooling (the natural log of mean hourly wages for our five education groups). The quality and quantity of education can also determine whether or not children are educated. To capture the availability of schools, we include the proportion of villages within a district that have a primary, middle, and high school. The quality of schools is measured by the teacher-pupil ratio in primary, middle, and high schools in a given state.[10]

[8] There are five education groups – less than primary, primary, middle, high school, and college education. We include dummies for the latter four levels and choose less than primary education as the omitted group.

[9] The head count ratio is defined as the proportion of individuals in a district whose monthly income falls below state- and sector-specific poverty lines. Poverty lines (in Rupees per capita per month) for rural and urban sectors within each state are obtained from the Planning Commission of the Government of India.

[10] State-level rather than district-level measures of the quality of education are included since district-level measures are not available for India.

IV RESULTS

1. Regression Results

Before summarizing the social propensities toward children's activities, which is the focus of this study, we briefly discuss the results of our regressions. Tables 4, 5, and 6, which report the means and standard deviations of the posterior distributions of regression coefficients, evaluated at the sample mean values of the covariates. A * represents variables for which the 95% posterior probability interval does not include zero.

Household-level variables are significantly correlated with all three outcomes – i.e. school, work, and idleness. A higher proportion of girls and boys in a household make schooling, child labor, and idleness more likely for children in that household. Gender differences, however, are evident on closer analysis: more boys in relation to girls increases participation in school and decreases participation in child labor and idleness. This captures the observed gender bias in children's activities in India. More educated father's and mother's increase participation in school and decrease participation in work and idleness. Low caste and Muslim children are less likely to attend school and more likely to work or remain idle, reflecting the disadvantage and possibly discrimination faced by these two groups. Children living in urban areas have a considerable advantage over rural children for participation in all three activities. Our measure of household income (the natural log of per capita monthly household expenditure) is positively correlated with schooling and negatively correlated with idleness, but has no correlation with child labor. On the other hand, land ownership by the household, which is also a measure of economic status, makes schooling more likely and idleness less likely but also raises the likelihood of child labor.

Our district-level measure of the quantity of primary schools in a district is negatively correlated with schooling and positively correlated with child labor. Though this result appears counter-intuitive at first, it could have at least two possible explanations. First, perhaps a higher number of primary schools come at the expense of the *quality* of primary education – i.e. fewer and less qualified teachers, absentee teachers, inadequate school buildings and equipment, etc.. Another explanation for this result may be that the current education policy with respect to the number of primary schools is being targeted at the wrong districts. If a district has an unfavorable social propensity towards schooling, construction of new schools may be ineffective in increasing school attendance and retention in that district. The proportion of villages with one or more high schools in a district is however negatively correlated with child labor and idleness, as expected. We find that a higher teacher-pupil ratio in primary schools in a state is negatively correlated with schooling and positively correlated with idleness. States with a higher number of children attending school and fewer number remaining idle will by definition have a lower teacher-pupil ratio. Thus, we should observe these correlations.

The head count ratio in a district has no correlation with schooling but is negatively correlated with child labor and positively correlated with idleness. Since the head count ratio measures the *absolute* poverty in a district – i.e. the proportion of individuals whose expenditure falls below their respective state-level poverty line – it may not be capturing the *severity* of poverty in that district. Absolute poverty may result in children being idle: prohibitively high schooling expenses may prevent children from attending school, but at the same time household poverty may not be so extreme that they need to send their children to work. The returns to unskilled labor captures an income effect that dominates any substitution effect. Since the majority of households who send their children to work or let them remain idle have at least one parent with less than primary education, higher returns to unskilled labor translates to higher parental income for these children. This decreases a household's reliance on children's incomes, even though schooling expenses may still be too high for these parents to afford education for their children. Thus, child labor may fall while idleness may rise.

Our spatial correlation parameter, ω, measures the degree of spatial dependence between social norms in adjacent districts. Our results indicate that social norms only with respect to schooling are significantly correlated among adjacent districts. Even though social norms may be an important determinant of child labor and idleness, we find that neighboring districts don't share similar social attitudes with respect to these activities.

2. Social Propensities Toward School, Work, and Idleness

Our main interest in this paper is in the distribution of district-level social norms, γ_d, which is obtained not only from the village-level random effects δ_{vd} within each district d but also from the district-level effects of other districts in the country. We summarize the posterior distribution of the relative ranks of γ_d in order to identify two groups of districts – the first where schooling is most likely to increase as a result of less idleness and the second where child labor is most likely to decrease in response to government policies.

We examine schooling and idleness separately from child labor for the following reasons. First, as shown in Figures 1, 2, and 3, there is large overlap of districts that have low levels of schooling as well as high levels of idleness. However, child labor is high in a very different group of districts.[11] Thus, in most districts where schooling is low, idleness is also high but child labor is not necessarily high. This observation suggests that districts where social attitudes oppose schooling and favor idleness may not necessarily have social norms that find child labor acceptable. Second, previous literature has shown that poverty and credit constraints are the driving force behind child labor. On the other hand, low returns to schooling, high unemployment of educated labor, insufficient schools, and inferior school quality may discourage children from attending school and encourage them to remain idle. Thus, one set of policies may be necessary to move idle children into school and another set may be required to stop children from working. For example, the former set of policies may include improving the quality and quantity of schools, raising returns to education, and providing other monetary incentives for parents to educate their children (provision of meals in school, subsidies for school supplies, etc.). The latter set of policies must provide households with sufficient funds to stop their children from working even though this may not be sufficient to send these children to school. Such a policy, though extremely costly, may be the only alternative to a ban on child labor, which will most likely make displaced children worse off by either moving them into worse occupations or bringing them closer to starvation.

Since both sets of policies can be extremely costly, especially for developing countries, we identify a group of districts where policies that are pro-schooling and anti-idleness will most likely succeed as a result of social attitudes that favor schooling and oppose idleness. We also identify a group of districts where child labor can be more easily

[11] Data from the Census of India, 1991, is used to construct these maps since a census better represents aggregate patterns of children's activities than does a sample survey. The percentage of children attending school, engaged in main work (i.e. worked 6 months or more during the year), and those who neither attended school nor worked are mapped. 1991 is the latest year for which census data on schooling, child labor, and idleness is currently available for India.

reduced since social norms oppose child work. Rather than attempt to change social attitudes towards children's activities, we propose that these two groups of districts be targeted by government policies.

We use the distribution of the posterior predictions of the mean village-level effects within a district, γ_d, to create a posterior distribution of ranks for all districts (Laird & Louis 1989, Hogan & Tchernis 2004). At each of the last 5000 iterations we rank the draws from the distribution of the posterior predictions of the district effect, which can be viewed as the draws from the posterior distribution of ranks of social norms. We summarize the distribution of ranks by computing the probability of being in top and bottom quintiles of the distribution for each district. We thus generate six different probabilities for each district d - i.e. the probabilities that the social propensity towards schooling, child labor, and idleness lie in the top 20% (top-school, top-work, and top-idle) and bottom 20% (bottom-school, bottom-work, and bottom-idle) of their respective posterior rank distributions.

We identify the first group of districts – i.e. those where policies that promote schooling and decrease idleness will most likely succeed – by finding districts that have a high social propensity towards schooling *and* a low social propensity towards idleness. To do this we identify a group of 26 districts in Table 7 where top-school and bottom-idle are *both* between 90% and 100% (5 districts), 80% and 90% (4 districts), 70% and 80% (6 districts), and 60% and 70% (11 districts). The group of districts where top-school and bottom-idle are both over 90% are most likely to respond to pro-school policies since social attitudes are most favorable to education and least favorable to idleness in these districts. Table 8 presents a group of 38 districts where anti-child-labor policies are most likely to succeed – i.e. where bottom-ftw is between 90% and 100% (6 districts), 80%

and 90% (9 districts), 70% and 80% (12 districts), and 60% and 70% (11 districts) – since social attitudes do not favor child labor in these districts. These districts have a low social propensity towards child labor and will most likely respond to policies that aim to reduce child work.

V CONCLUSION

The primary contribution of our paper lies in isolating the effects of culture and social attitudes towards children's activities, after controlling for a wide range of socio-economic determinants of child labor, schooling, and idleness. The relevance of our analysis lies in the realization that if children's participation in work, school, or neither has strong cultural connotations, policy prescriptions are very different than if children's activities are driven entirely by poverty, school access and quality, and household socio-economic variables. If culture plays a significant role in determining children's activities then policies that attempt to change social attitudes in favor of education and against idleness and child labor become increasingly important. However, changing social attitudes is a gradual and long term and non-trivial process. Therefore, rather than prescribe policies that attempt to make individuals place greater value on education and oppose idleness and child work, which we believe should be implemented over the long term, we suggest using more standard policies in the short run. In addition, instead of implementing these policies throughout the country, we suggest focusing on a small group of districts where our analysis predicts these policies will be most effective.

For the first group of districts – i.e. those that we identify as being pro-schooling and anti-idleness – policies that improve the quantity and quality of schools may be extremely successful. Building new schools, hiring more and better teachers, investing in school supplies and infrastructure, improving transportation to and from schools, and providing school meals are all policies that can make parents more likely to send their children to school rather than let them remain idle. This is especially true if these parents favor schooling and oppose idleness and keep their children out of school because of a scarcity of schools, inadequate quality of education, or poor infrastructure. For the group of districts that are anti-child-labor, we suggest policies that can help parents remove their children from the labor market. Providing these parents with part or all of their children's wages will enable them to stop their children from working. Moreover, providing free part- or full-time education to these children in addition to their foregone wages can greatly improve their future earning ability.

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Table 1: Proportion of Children 5-14 Years Engaged in Work, School, & Neither Work Nor School in India: 1999-2000

Activity	**All Children**	**Boys**	**Girls**
Work	5.16	3.29	7.24
School	67.92	71.25	64.22
Idle	19.87	18.24	21.69
Work & School	0.83	0.81	0.85
Work & Idle	0.47	0.45	0.49
School & Idle	5.75	5.95	5.51

Source: National Sample Survey, Employment & Unemployment Schedule, Round 55.

Table 2: Proportion of Children 5-14 Years Engaged in Work, School, & Neither Work Nor School in Indian States: 1999-2000

State/Union Territory	**All Children**			**Boys**			**Girls**		
	Work	School	Idle	Work	School	Idle	Work	School	Idle
Andhra Pradesh	8.94	65.88	12.77	6.75	69.21	11.23	11.29	62.31	14.43
Arunachal Pradesh	4.39	43.78	39.75	3.73	42.37	42.03	5.12	45.35	37.19
Assam	3.00	68.43	20.85	2.66	70.21	18.57	3.37	66.45	23.38
Bihar	5.84	50.45	42.20	3.92	55.31	38.96	8.16	44.58	46.10
Goa	1.14	48.30	13.83	0.70	49.30	13.64	1.65	47.11	14.05
Gujarat	5.91	44.35	18.20	2.43	47.39	16.71	9.77	40.98	19.84
Haryana	3.61	82.35	13.59	2.04	84.78	12.75	5.36	79.64	14.52
Himachal Pradesh	1.90	92.47	5.37	0.75	94.16	4.84	3.18	90.59	5.95
Jammu & Kashmir	2.37	78.13	15.38	0.81	81.14	13.45	4.17	74.66	17.62
Karnataka	8.71	74.99	14.04	6.89	76.82	14.13	10.58	73.10	13.95
Kerala	0.37	90.95	4.80	0.18	91.05	4.75	0.56	90.85	4.86
Madhya Pradesh	6.27	62.68	26.70	4.21	66.95	24.25	8.59	57.86	29.45
Maharashtra	3.74	67.46	12.19	2.37	69.12	11.85	5.20	65.69	12.55
Manipur	1.12	74.14	11.05	1.32	75.07	9.82	0.88	73.02	12.52
Meghalaya	3.04	53.88	14.21	2.74	52.38	14.00	3.37	55.54	14.45
Mizoram	2.63	60.76	16.67	2.23	62.96	14.31	3.06	58.40	19.19
Nagaland	2.04	89.80	6.41	1.67	89.44	6.94	2.45	90.18	5.83
Orissa	5.24	69.84	23.57	2.56	73.86	22.06	8.00	65.70	25.12
Punjab	4.67	83.97	10.16	3.33	84.92	10.30	6.22	82.87	10.00
Rajasthan	9.66	71.76	18.44	4.78	81.68	13.33	15.29	60.29	24.34
Sikkim	2.54	85.93	11.13	2.59	85.98	10.98	2.49	85.88	11.30
Tamil Nadu	3.51	76.48	7.06	2.53	78.12	6.77	4.59	74.67	7.39
Tripura	1.43	86.78	11.78	1.06	88.49	10.45	1.98	84.32	13.70
Uttar Pradesh	5.65	66.37	24.91	3.20	71.92	21.63	8.43	60.06	28.64
West Bengal	4.50	71.67	19.99	2.53	73.89	19.83	6.56	69.33	20.15
Andaman & Nicobar Islands	1.73	77.23	21.04	1.68	78.77	19.55	1.79	75.60	22.62
Chandigarh	2.14	90.51	6.13	0.82	91.48	6.32	3.81	89.27	5.88
Dadra & Nagar Haveli	2.83	12.15	31.17	2.63	8.77	35.09	3.01	15.04	27.82
Delhi	2.70	85.13	8.46	1.95	87.23	7.98	3.52	82.81	8.98
Lakshadweep	0.81	95.12	4.07	1.59	93.65	4.76	0.00	96.67	3.33
Pondicherry	1.21	88.16	4.59	0.52	90.58	4.19	1.79	86.10	4.93
India	5.16	67.92	19.87	3.29	71.25	18.24	7.24	64.22	21.69

Source: National Sample Survey, Employment & Unemployment Schedule, Round 55.

Table 3: Proportion of Children 5-14 Years Engaged in Work, School, & Neither Work Nor School in Indian States: 1999-2000

Variable	Description	Level
Dependent		
school	1 if one or more child in a household attends school full time, 0 otherwise	household
work	1 if one or more child in a household works full time, 0 otherwise	household
idle	1 if one or more child in a household neither atends school nor works full time, 0 otherwise	household
Explanatory		
girls	number of female children in the household	household
boys	number of male children in the household	household
$father-primary$	1 if father completed primary school, 0 otherwise	household
$father-middle$	1 if father completed middle school, 0 otherwise	household
$father-high$	1 if father completed high school, 0 otherwise	household
$father-college$	1 if father completed college, 0 otherwise	household
$mother-primary$	1 if mother completed primary school, 0 otherwise	household
$mother-middle$	1 if mother completed middle school, 0 otherwise	household
$mother-high$	1 if mother completed high school, 0 otherwise	household
$mother-college$	1 if mother completed college, 0 otherwise	household
lowcaste	1 if household is lowcaste, 0 otherwise	household
muslim	1 if household is muslim, 0 otherwise	household
urban	1 if household lives in urban sector, 0 otherwise	household
expenditure	natural log of per capita monthly household expenditure	household
land	1 if household owns > 1 acre of land, 0 otherwise	household
$oct-dec$	1 if household was surveyed from October to December, 0 otherwise	household
$jan-march$	1 if household was surveyed from January to March, 0 otherwise	household
$april-june$	1 if household was surveyed from April to June, 0 otherwise	household
$primary-schools$	proportion of villages with 1 or more primary school	district
$middle-schools$	proportion of villages with 1 or more middle school	district
$high-schools$	proportion of villages with 1 or more high school	district
poverty	head count ratio	district
$lnhrwage- < primary$	natural log of average hourly wage of adults with less than primary education	district
$lnhrwage-primary$	natural log of average hourly wage of adults with primary education	district
$lnhrwage-middle$	natural log of average hourly wage of adults with middle school education	district
$lnhrwage-high$	natural log of average hourly wage of adults with high school education	district
$lnhrwage-college$	natural log of average hourly wage of adults with college education	district
$teacher-pupil-ratio-primary$	teacher-pupil ratio in primary schools	state
$teacher-pupil-ratio-middle$	teacher-pupil ratio in middle schools	state
$teacher-pupil-ratio-high$	teacher-pupil ratio in high schools	state

Table 4: Regression Results of Probit Estimation of Participation in School: India, 1999-2000

Variable (1)	**Mean** (2)	**Standard Deviation** (3)
constant	0.1161	0.1739
girls	0.0310	0.0020*
boys	0.0572	0.0028*
$father-primary$	0.0860	0.0074*
$father-middle$	0.1059	0.0072*
$father-high$	0.1195	0.0082*
$father-college$	0.1428	0.0136*
$mother-primary$	0.0391	0.0074*
$mother-middle$	0.0300	0.0090*
$mother-high$	0.0380	0.0104*
$mother-college$	0.0012	0.0141
lowcaste	-0.0475	0.0058*
muslim	-0.0618	0.0074*
urban	0.0439	0.0070*
expenditure	0.1033	0.0065*
land	0.0468	0.0048*
$oct-dec$	0.0312	0.0075*
$jan-march$	0.0281	0.0086*
$april-june$	0.0126	0.0079
$primary-schools$	-0.2335	0.0502*
$middle-schools$	0.1027	0.1090
$high-schools$	-0.0083	0.1175
poverty	-0.0497	0.0684
$lnhrwage- < primary$	-0.0207	0.0320
$lnhrwage-primary$	-0.0019	0.0366
$lnhrwage-middle$	0.0088	0.0321
$lnhrwage-high$	-0.0333	0.0261
$lnhrwage-college$	-0.0219	0.0316
$teacher-pupil-ratio-primary$	-0.0043	0.0011*
$teacher-pupil-ratio-middle$	-0.0015	0.0012
$teacher-pupil-ratio-high$	-0.0024	0.0012
spatial correlation parameter (ω)	0.0899	0.0228*
Number of Observations	49186	

Source: National Sample Survey, Employment & Unemployment Schedule, Round 55. Columns (2) and (3) report the means and standard deviations of the posterior distributions of regression coefficients, evaluated at the sample mean values of the covariates. A * represents variables for which the 95% posterior probability interval does not include zero.

Table 5: Regression Results of Probit Estimation of Participation in Child Labor: India, 1999-2000

Variable (1)	**Mean** (2)	**Standard Deviation** (3)
$constant$	-0.0426	0.0255
$girls$	0.0130	0.0009*
$boys$	0.0032	0.0006*
$father-primary$	-0.0213	0.0023*
$father-middle$	-0.0284	0.0028*
$father-high$	-0.0417	0.0034*
$father-college$	-0.0593	0.0059*
$mother-primary$	-0.0318	0.0034*
$mother-middle$	-0.0420	0.0045*
$mother-high$	-0.0534	0.0051*
$mother-college$	-0.0553	0.0127*
$lowcaste$	0.0083	0.0019*
$muslim$	0.0122	0.0021*
$urban$	-0.0072	0.0019*
$expenditure$	-0.0038	0.0020
$land$	0.0083	0.0018*
$oct-dec$	-0.0062	0.0022*
$jan-march$	-0.0094	0.0024*
$april-june$	-0.0087	0.0023*
$primary-schools$	0.0331	0.0086*
$middle-schools$	0.0167	0.0206
$high-schools$	-0.0330	0.0144*
$poverty$	-0.0387	0.0101*
$lnhrwage- < primary$	-0.0156	0.0065*
$lnhrwage-primary$	0.0041	0.0043
$lnhrwage-middle$	-0.0062	0.0040
$lnhrwage-high$	-0.0042	0.0045
$lnhrwage-college$	-0.0082	0.0050
$teacher-pupil-ratio-primary$	0.0004	0.0002
$teacher-pupil-ratio-middle$	0.0004	0.0002
$teacher-pupil-ratio-high$	-0.0001	0.0001
spatial correlation parameter (ω)	0.0044	0.0295
Number of Observations	49186	

Source: National Sample Survey, Employment & Unemployment Schedule, Round 55. Columns (2) and (3) report the means and standard deviations of the posterior distributions of regression coefficients, evaluated at the sample mean values of the covariates. A * represents variables for which the 95% posterior probability interval does not include zero.

Table 6: Regression Results of Probit Estimation of Participation in Neither Work Nor School: India, 1999-2000

Variable (1)	**Mean** (2)	**Standard Deviation** (3)
$constant$	-0.0621	0.0848
$girls$	0.0649	0.0023*
$boys$	0.0553	0.0021*
$father-primary$	-0.0867	0.0070*
$father-middle$	-0.1024	0.0071*
$father-high$	-0.1273	0.0078*
$father-college$	-0.1556	0.0129*
$mother-primary$	-0.0522	0.0075*
$mother-middle$	-0.0604	0.0087*
$mother-high$	-0.0631	0.0118*
$mother-college$	-0.0354	0.0173*
$lowcaste$	0.0473	0.0051*
$muslim$	0.0524	0.0064*
$urban$	-0.0420	0.0070*
$expenditure$	-0.1142	0.0057*
$land$	-0.0390	0.0052*
$oct-dec$	0.0056	0.0076*
$jan-march$	0.0191	0.0076*
$april-june$	0.0620	0.0083*
$primary-schools$	0.0426	0.0301
$middle-schools$	0.0236	0.0693
$high-schools$	-0.1253	0.0527*
$poverty$	0.2128	0.0328*
$lnhrwage- < primary$	0.0458	0.0236*
$lnhrwage-primary$	-0.0188	0.0179
$lnhrwage-middle$	-0.0038	0.0176
$lnhrwage-high$	0.0026	0.0152
$lnhrwage-college$	0.0147	0.0189
$teacher-pupil-ratio-primary$	0.0062	0.0006*
$teacher-pupil-ratio-middle$	-0.0021	0.0007*
$teacher-pupil-ratio-high$	-0.0008	0.0005
spatial correlation parameter (ω)	0.0132	0.0304
Number of Observations	49186	

Source: National Sample Survey, Employment & Unemployment Schedule, Round 55. Columns (2) and (3) report the means and standard deviations of the posterior distributions of regression coefficients, evaluated at the sample mean values of the covariates. A * represents variables for which the 95% posterior probability interval does not include zero.

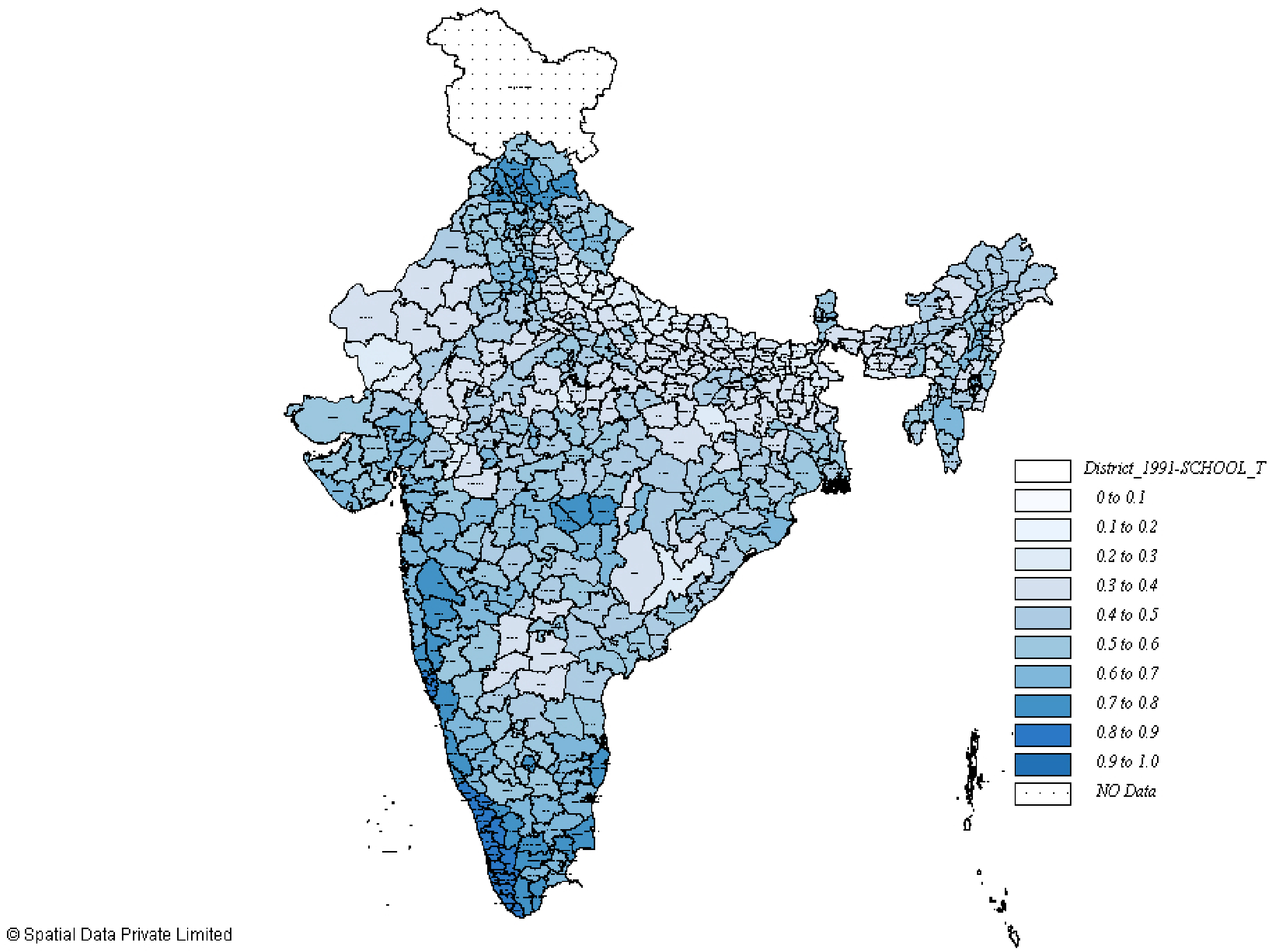

Figure 1: Proportion of Children Attending School: Indian Districts, 1991

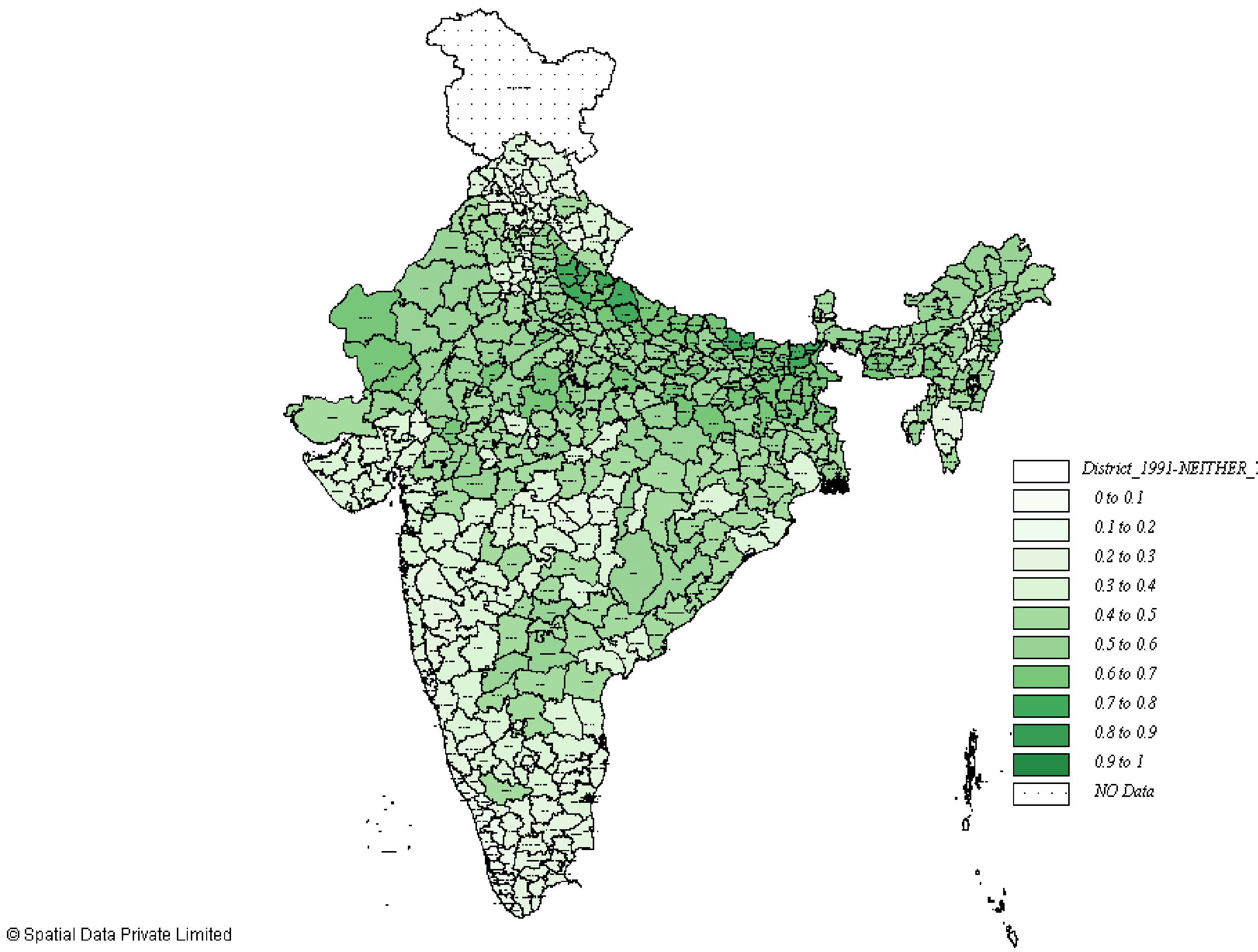

Figure 2: Proportion of Children Neither Attending School Nor Working: Indian Districts, 1991

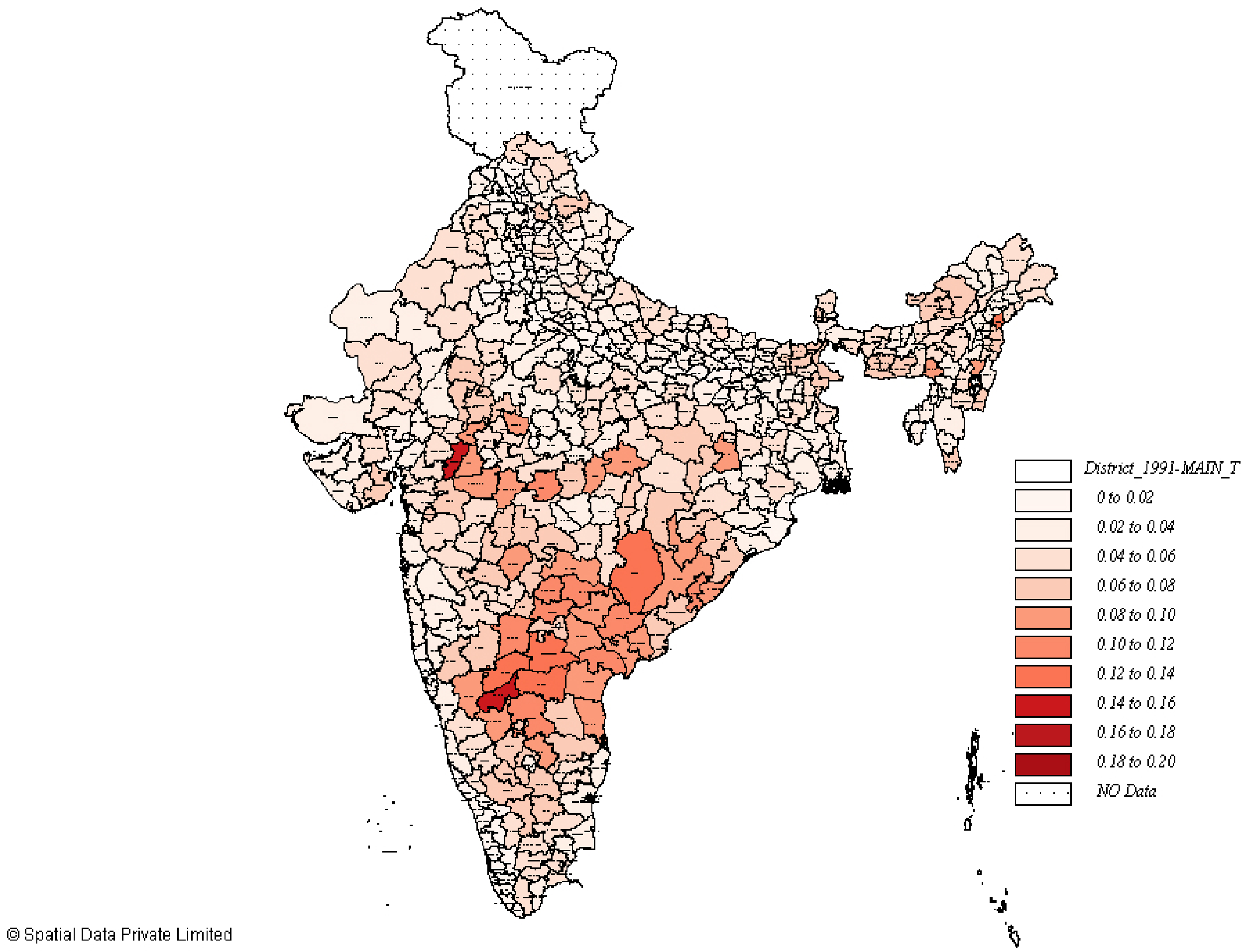

Figure 3: Proportion of Children Engaged in Child labor: Indian Districts, 1991

Table 7: Pro-Schooling and Anti-Idleness Districts: India, 1999-2000

Cutoff (%)	**District**	**State**	**Schooling(%)**			**Idleness(%)**		
			All	Boys	Girls	All	Boys	Girls
90	Warangal	Andhra Pradesh	46.87	55.24	37.97	42.74	35.95	49.95
90	Kodagu	Karnataka	64.70	67.49	61.85	29.49	26.86	32.18
90	Chhindwara	Madhya Pradesh	45.92	50.72	40.99	43.62	39.27	48.07
90	Pali	Rajasthan	43.39	59.11	25.42	51.35	37.66	67.01
90	Dungarpur	Rajasthan	32.21	42.97	21.00	59.85	50.75	69.34
80	Idukki	Kerala	83.11	83.30	82.92	16.23	16.03	16.43
80	Vidisha	Madhya Pradesh	48.70	55.55	40.63	45.82	37.27	55.90
80	Cuttack, Jagatsinghpur	Orissa	60.55	65.34	55.60	38.21	32.83	43.78
80	Mongam	Sikkim	54.63	56.73	52.45	40.19	38.34	42.10
70	Shahdol	Madhya Pradesh	40.42	49.02	31.41	51.65	43.44	60.24
70	Chhimtuipui	Mizoram	45.42	48.50	42.26	44.40	41.94	46.93
70	Zunheboto	Nagaland	46.50	48.58	44.39	49.03	47.21	50.87
70	Nagaur	Rajasthan	34.65	49.61	18.05	58.82	45.71	73.38
70	Udaipur, Rajsamand	Rajasthan	37.26	48.80	25.10	55.68	45.52	66.38
70	Chittaurgarh	Rajasthan	35.48	48.06	22.03	54.80	44.33	65.98
60	Darrang, Sonitpur	Assam	41.02	44.25	37.65	52.19	47.84	56.73
60	Sitamarhi	Bihar	25.35	32.11	17.02	71.41	62.66	82.20
60	Bhavnagar	Gujarat	55.79	61.76	49.40	35.78	29.07	42.98
60	Valsad	Gujarat	63.07	65.40	60.63	31.92	29.80	34.14
60	Sidhi	Madhya Pradesh	32.47	43.79	20.18	59.03	48.60	70.36
60	Lunglei	Mizoram	55.97	57.18	54.74	33.86	32.88	34.85
60	Wokha	Nagaland	64.32	65.58	63.02	33.72	32.75	34.72
60	Ajmer	Rajasthan	49.66	61.91	35.97	42.77	32.33	54.43
60	Kanniyaikumari	Tamil Nadu	82.19	82.24	82.14	16.47	16.22	16.74
60	Ballia	Uttar Pradesh	39.68	48.09	29.85	57.46	48.67	67.75
60	Haora	West Bengal	53.22	55.35	51.03	44.54	40.92	48.26

Source: National Sample Survey, Employment & Unemployment Schedule, Round 55. Some districts are grouped together since these have split into two or more districts since 1999-2000. The last six columns report the actual proportion of children, boys, and girls who attend school and are idle in these districts.

Table 8: Anti-Child-Labor Districts: India, 1999-2000

Cutoff (%)	**District**	**State**	**Child Labor(%)**		
			All	Boys	Girls
90	Dharwad	Karnataka	8.93	9.63	8.20
90	Alappuzha	Kerala	0.23	0.24	0.23
90	Bolangir, Sonepur	Orissa	6.03	9.00	3.03
90	Chittaurgarh	Rajasthan	6.74	6.42	7.07
90	Gyalshing	Sikkim	7.01	6.46	7.57
90	Tiruchirappalli	Tamil Nadu	4.09	3.91	4.27
80	Dibang Valley	Arunachal Pradesh	5.31	4.65	6.08
80	Samastipur	Bihar	2.28	3.58	0.76
80	Ranchi	Bihar	4.93	5.15	4.70
80	Gandhinagar	Gujarat	1.15	1.42	0.85
80	Chhindwara	Madhya Pradesh	7.76	8.84	6.66
80	Bombay	Maharashtra	1.15	1.66	0.60
80	Osmanabad	Maharashtra	4.77	4.63	4.93
80	Latur	Maharashtra	5.52	5.80	5.23
80	Bhilwara	Rajasthan	7.43	6.97	7.93
70	Junagadh	Gujarat	3.24	4.25	2.17
70	Vadodara	Gujarat	4.09	5.27	2.79
70	Sirampur	Himachal Pradesh	6.76	6.17	7.38
70	Mandhya	Karnataka	6.55	8.80	4.32
70	East Nimar	Madhya Pradesh	8.43	9.11	7.68
70	Amravati	Maharashtra	4.32	4.54	4.09
70	Jaintia Hills	Meghalaya	9.51	11.84	7.21
70	Ganjam, Gajapati	Orissa	6.04	7.05	5.01
70	Pali	Rajasthan	3.15	2.58	3.81
70	Kota, Baran	Rajasthan	2.61	3.15	1.99
70	Basti, Sidharthanagar	Uttar Pradesh	3.08	4.30	1.71
70	Hooghly	West Bengal	2.36	3.57	1.10
60	Sibsagar, Golaghat, Jorhat	Assam	3.37	3.64	3.09
60	Bhind	Madhya Pradesh	1.52	2.52	0.23
60	Shajapur	Madhya Pradesh	5.90	7.15	4.50
60	Mandla	Madhya Pradesh	8.41	7.47	9.39
60	Bishnupur	Manipur	1.60	1.29	1.91
60	Cuttack, Jagatsinghpur	Orissa	1.07	1.70	0.42
60	Jaipur, Dausa	Rajasthan	2.88	2.73	3.05
60	North Arcot	Tamil Nadu	4.40	4.73	4.06
60	Azamgarh, Maunath Bhanjan	Uttar Pradesh	2.48	3.19	1.72
60	Jaunpur	Uttar Pradesh	1.80	2.42	1.12
60	Ballia	Uttar Pradesh	2.17	2.74	1.50

Source: National Sample Survey, Employment & Unemployment Schedule, Round 55. Some districts are grouped together since these have split into two or more districts since 1999-2000. The last three columns report the actual proportion of children, boys, and girls who work in these districts.