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Rubiana Chamarbagwala
Indiana University, Bloomington, rchamarb@indiana.edu

Rusty Tchernis
Georgia State University, rtchernis@gsu.edu

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Rubiana Chamarbagwala
Indiana University, Bloomington

Rusty Tchernis
Georgia State University

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Georgia State University
Andrew Young School of Policy Studies

Exploring the Spatial Determinants of Children's Activities: Evidence from India

Rubiana Chamarbagwala* Rusty Tchernis†

August, 2009

Abstract

This paper investigates the choice of children's activities in India and provides recommendations for areas where policy intervention to promote schooling and combat child labor would be most successful. First, we recognize that child schooling and labor are not the only activities that children can engage in and include idleness as one of the choices. Second, we use a hierarchical model with spatially correlated random effects to analyze the determinants of the choice of children's activities. Lastly, we recommend that pro-schooling intervention be implemented in districts with favorable attitudes towards schooling and unfavorable attitudes towards idleness, while anti-child-labor interventions be implemented in districts where attitudes towards child labor are less favorable. We thus identify two groups of Indian districts to target appropriate government interventions.
JEL Codes: I20, J24
Keywords: Child Labor, Education, Idleness, Spatial Dependence, India

*Department of Economics, Wylie Hall, Room 105, 100 S. Woodlawn, Indiana University, Bloomington, IN 47405, USA. E-mail: rchamarb@indiana.edu

†Department of Economics, Andrew Young School of Policy Studies, Georgia State University, P.O. Box 3992, Atlanta, GA 30302-3992, USA. E-mail: rtchernis@gsu.edu

1 INTRODUCTION

It is well established that education is critical in generating and sustaining economic development. According to the United Nations (1948), education also constitutes a basic human right of every child. Nevertheless, the 2001 census of India shows that more than 90 million Indian children are not attending school.[1] Whatever the reasons are for children not attending school but instead remaining idle or working, government policies can be used to improve human capital investments. In addition to making primary education free in public schools, India's efforts to increase schooling include a variety of programs that aim to improve the quality and quantity of schools. These include the Operation Blackboard, District Primary Education, and School Meal programs, among others. Despite these efforts, a large proportion of Indian children remain uneducated, a reason for which could be incorrect targeting of these policies. If unobservable factors make certain households less likely to send their children to school but more likely to keep them idle or send them to work, then neither otherwise sound education policies nor child labor laws can be effective in improving these children's human capital prospects.

In this paper, we summarize the *unexplained* component of parents' decisions to send their children to school, work, or neither school nor work in India. Rather than focus solely on schooling and child labor as the only activities available to children, one of our contributions to the existing literature is that we include idleness as a third activity that children may engage in.[2] This assumption is supported by empirical evidence for India, where approximately 20% of children are idle compared to 5% engaged in child

[1]In the 5-14 age-group, 90,465,708 children don't attend school full time or part time. Of these 43,232,941 are boys and 47,243,455 are girls. These constitute 36% of all children, 33% of boys, and 39% of girls.

[2]For India, 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 India and Ghana.

labor.[3] Accounting for the possibility that children may remain idle is crucial to the formulation of sound policies. Policies that reduce child labor may not necessarily result in more schooling if formerly working children remain idle rather than attend school.

Our controls include not only the socio-economic determinants of children's activities, but also measures of the quality and quantity of education and the returns to schooling within a region. We capture the unexplained component of parents' decisions regarding their children's activities in a village-level random effect. Allowing for spatial correlation of district-level random effects, we summarize a district's unexplained propensity towards schooling, child labor, and idleness. A district's unexplained propensity towards an activity may be determined by omitted economic variables that are difficult to measure. These include, amongst other factors, parents' expectations of future returns to schooling and job opportunities for educated labor as well as the quality of education available to children. However, non-economic location-specific factors, such as social norms or culture, may also determine a district's unexplained propensity towards children's activities.

While our analysis does not provide evidence that social norms alone determine districts' unexplained propensities towards children's activities, it is very likely that social factors explain these unexplained propensities to some extent. It is well established that social norms can play a crucial role even in economic decision making as individuals rarely choose their actions in isolation but embedded within their social context (Bongaarts & Watkins 1996, Rosero-Bixby & Casterline 1993, 1994, Montgomery & Casterline 1993, Watkins & Danzi 1995).[4] According to Bongaarts & Watkins (1996), three distinct aspects constitute social interactions – the exchange of information and ideas, the joint evaluation of their meaning in a given context, and social influence that

[3] These figures are based on calculations using National Sample Survey Organization data for the year 1999-2000 in India.

[4] This literature primarily deals with the role of social interactions, both social learning and social influence, on fertility decisions.

encourages or constrains behavior and actions. Thus, 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 may therefore reduce the willingness of households to send their children to work. Moreover, through interaction with others, individuals may change their own attitudes, perceptions, and preferences and – unless their actual behavior is determined by binding constraints – this may influence their actions.

Our primary contribution is to prescribe detailed policy recommendations in order to improve human capital investments in India, based on both observable and unobservable determinants of children's activities. We identify two groups of districts – one where government interventions 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 has both a high unexplained propensity towards schooling and a low unexplained propensity towards idleness for children. According to our analysis, these districts most likely embody attitudes that are favorable to schooling and oppose idleness. 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. In the second group of districts, parents have a low unexplained propensity towards sending their children to work, making parents more likely to respond to anti-child-labor programs.

The following section briefly discusses the related literature and Section 3 describes our data. Section 4 formalizes the empirical model and discusses the empirical methodology. Results are presented in section 5 and section 6 concludes with policy implications.

2 LITERATURE REVIEW

Many authors have examined parents' decisions whether 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 even for relatively skilled labor (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.

With respect to previous theoretical and empirical research, there are few studies that address the non-economic determinants of children's activities. 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 empirically 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.

This paper differs from the existing literature by allowing for spatial correlation in schooling, child labor, and idleness decisions. Spatial dependence or spatial correlation exists when a variable exhibits a systematic pattern rather than a random assignment across space. 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 are each examined separately in order to measure the unexplained inclination towards each of these activities.

We summarize the posterior distribution of ranks of district-level random effects, which measures the unexplained 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 *unexplained 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. Spatial correlation of district-level unobservables has implications for policy as well. If policies are effective in the two groups of districts presented in this paper, there may be positive spillovers into neighboring districts, neighbors' neighbors, and so on throughout the country. Over time, therefore, the entire economy may benefit from targeted intervention.

3 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 predictors 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.[5] 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 allow 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

[5] 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.

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 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.[6]

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.

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 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.

[6]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. Similarly, using the usual activity of children during the past year to measure school, work, and idleness provides qualitatively similar results.

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. Idle 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.

4 EMPIRICAL METHODOLOGY

4.1 Estimation

We incorporate spatial correlation into schooling, child labor, and idleness decisions for children by allowing these outcomes in a given location to depend on the outcomes at neighboring locations. We estimate a model where location-specific economic and non-economic factors operate and potentially influence parental decisions regarding school, work, and idleness for their children. To do this we include a village- or urban-block-level random effect, which assumes that all households within the same village or urban block share a common unexplained propensity towards school, work, and idleness.[7] We allow for heteroskedasticity of village-level random effects within a district since all villages within a district may not be identical in terms of unexplained propensities towards children's activities. To capture correlations among location-specific unobservable determinants of children's activities, we assume that there are spatially correlated unobservables among adjacent districts so that neighboring districts share similar unexplained propensities towards children's activities.[8]

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

[7]The urban equivalent of a village is an urban-block in the NSS data. Since our analysis includes both rural and urban areas, we include urban-block-level random effects for urban areas. We use the term *village* to represent both villages and urban blocks in the rest of the paper. The entire country consists of 35 states and union territories, which in turn consists of districts. Each district comprises several villages and urban blocks. The average number of blocks in a district is 29 villages (rural blocks) and 35 urban blocks in our data with an average of 7.3 households per block in both rural and urban areas.

[8]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 district level, it should also exist at more disaggregate (village) levels. We thus model spatial correlation at the district-level, which our data allows us to do.

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 village-level propensities towards child labor, schooling, or idleness. The village-level random effect δ_{vd} is normally distributed with mean γ_d and variance σ_d^2. These two parameters capture the mean and variance of village-level propensities 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 model spatial correlation using a conditionally autoregressive (CAR) model (Besag 1974, Sun et al. 1999, Wall 2004).

We estimate the following hierarchical model with 3 levels:

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

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

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

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 unexplained propensities 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 spatial parameter, ω, measures the marginal contribution of the random effects in the neighboring districts on the random effect in district j. 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 values of τ represent less spatial dependence, meaning that conditional on a district's neighbors' values of γ there is still a lot of variability in the distribution of γ_d.[9] Since the dependent variable is at the household level but we only have spatial information at the district level we cannot use spatial probit models, as in Beron & Vijverberg (2004) and LeSage & Kelley Pace (2009).

The specification in Equation (3) results in a joint distribution for all districts, $\gamma \sim N(0, B)$, where $B = (I_D - \omega W)^{-1}T$ (Besag 1974) and 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 district's dependence on it's adjacent neighbors, the marginal representation shows that all the districts in the country are correlated.[10] 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 explanatory variables included in X_{hvd} and described in Table 3 include household-

[9]As mentioned in the Introduction, there is theoretical and empirical justification for assuming a priori that location-specific unobservables may influence economic outcomes, and that these unobservables may be spatially correlated (Bongaarts & Watkins 1996, Rosero-Bixby & Casterline 1993, 1994, Montgomery & Casterline 1993, Watkins & Danzi 1995).

[10]A district's unexplained propensity towards an activity is correlated with it's adjacent neighbors' unexplained propensities, it's neighbors' neighbors unexplained propensities, and so on throughout the entire country.

, 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,[11] 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)[12] and returns to schooling (the natural log of mean hourly wages for our five education groups in both urban and rural sectors). 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.[13]

4.2 Sampling Algorithm

We estimate the posterior distribution of the parameters of the model using the Markov Chain Monte Carlo simulation methods, specifically the Gibbs sampler (A.E. & Smith 1990, Casella & George 1992) and the Metropolis-Hastings algorithm (Chib & Greenberg

[11] 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.

[12] 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.

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

1995). The Gibbs sampler allows us to obtain a sample of draws from the marginal posterior distributions of the parameters by sequentially sampling from the posterior distributions, conditional on the latest draws of the other parameters. We follow Chib and Greenberg (1998) and augment the parameter vector, θ, to include the latent y^*, and the random effects, δ and γ, so that $\theta = \{\beta, y^*, \delta, \gamma, \omega, \sigma, \tau\}$.

We use diffuse conjugate prior densities described in the Appendix. The conditional posterior for β, y^*, δ, and γ are Normal, and for σ and τ are Inverse Gamma and are simple to sample from. The only parameter for which the conditional posterior distribution does not have a closed form is ω and we use Metropolis-Hastings algorithm to sample from it. The exact posterior distributions are given in the Appendix.

5 RESULTS

5.1 Regression Results

Before summarizing the unexplained 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 report the means and standard deviations of the posterior distributions of marginal effects, 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. Gender differences exist with respect to household composition – the likelihood of school participation increases more with an additional boy compared to an additional girl while this relationship is reversed for participation in child labor and idleness. This captures the observed gender bias in children's activities in India. More educated fathers and mothers 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 are more likely to attend school and less likely to work or be idle compared to children living in rural areas. 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. The latter result is consistent with the findings of Bhalotra & Heady (2003) for girls but not for boys in Ghana.[14].

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 is misguided in that primary schools are being constructed in the *wrong* districts. If a district has an unfavorable attitude 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. Again, this result is contrary to our expectations and may be the result of misguided policy – teachers may be placed in the *wrong* districts.

[14]The authors refer to this result as a wealth paradox since girls from land-rich households, though wealthier, are more likely to work than girls in land-poor households, which is evidence that child labor is not completely poverty-driven

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. Thus, higher unskilled wages are associated with less child labor and more idleness. 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 into 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 unexplained propensities towards an activity among districts. In other words, ω measures the marginal contribution of the random effects in the neighboring districts on the random effect in district j. Our results indicate that only unexplained propensities towards schooling exhibit substantial spatial correlation, which is strictly positive and is at the very boundary of the support for ω. As discussed in the Introduction, it is not only social norms that determine districts' unexplained propensities towards schooling decisions. However, it is very likely that social factors explain these unexplained propensities to some extent. Even though omitted variables may be an important determinant of child labor and idleness, we find that neighboring districts don't share similar unexplained propensities with respect to these activities.

5.2 Unexplained Propensities Toward School, Work, and Idleness

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.[15] 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 attitudes oppose schooling and favor idleness may not necessarily have attitudes 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,

[15] 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.

we identify a group of districts where policies that are pro-schooling and anti-idleness will most likely succeed as a result of unexplained propensities that favor schooling and oppose idleness. We also identify a group of districts where child labor can be more easily reduced since unexplained propensities oppose child work. Rather than attempt to change parental attitudes towards children's activities, we propose that these two groups of districts be targeted by government policies.

In order to prescribe district-specific policy recommendations, we focus on the distribution of district-level unexplained propensities, γ_d, which are informed not only by the village-level random effects δ_{vd} within each district d but also by 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 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 iteration 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 unexplained propensities. 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 unexplained 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 unexplained propensity towards schooling *and* a low unexplained propensity towards idleness. To do this we identify a group of 25 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% (10 districts). These districts have a high unexplained propensity towards schooling as well as a low unexplained propensity towards idleness and will most likely respond to policies that aim to increase schooling. Table 8 presents a group of 37 districts where anti-child-labor policies are most likely to succeed – i.e. where bottom-work is between 90% and 100% (5 districts), 80% and 90% (9 districts), 70% and 80% (12 districts), and 60% and 70% (11 districts). These districts have a low unexplained propensity towards child labor and will most likely respond to policies that aim to reduce child work.

6 CONCLUSION

The primary contribution of our paper lies in measuring and summarizing the unexplained component towards children's activities, after controlling for a wide range of socio-economic determinants of child labor, schooling, and idleness in Indian districts. The relevance of our analysis lies in the realization that if children's participation in work, school, or idleness has even some non-economic 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. While we do not claim and cannot provide evidence that a district's unexplained propensity towards an activity is driven entirely by social norms, it is reasonable to assume that at least some part of the unexplained component is influenced by social acceptance and rejection of schooling, child labor, or idleness. If one's social context 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 may increasingly important. However, changing social attitudes is a gradual, 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 should remain a long-term policy goal, 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 example, pro-schooling and anti-idleness propensities are highest in Warangal (Andhra Pradesh), Kodagu (Karnataka), and Chhindwara (Madhya Pradesh), so pro-schooling policies may be most effective in these districts. On the other hand, anti-child-labor policies may most likely succeed in Dharwad (Karnataka), Bolangir and Sonepur (Orissa), and Chittaurgarh (Rajasthan) – which are the districts with the most anti-child-labor propensities.

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.

7 APPENDIX

7.1 Sampling Algorithm

We can rewrite the model in the vector notation

$$\begin{aligned} Y^* &= X\beta + C\delta + \epsilon,\ \epsilon \sim N(0,1) \\ \delta &\sim N(Q\Gamma, \Sigma) \\ \Gamma &\sim N(0_D, (I-\omega W)^{-1}T), \end{aligned}$$

where Y^* is the stacked vector of $y^*_{hvd}, h = 1, \ldots, H, v = 1, \ldots, V$, and $d = 1, \ldots, D, C$ is an indicator matrix of size $H \times V$ with elements $C_{hv} = 1$ if household h is located in village v, where Q is an indicator matrix of the size $V \times D$ with elements $Q_{vd} = 1$ if village v is located in village d, and $\Sigma = diag(Q\{\sigma^2_d\}),\ T = I_D\tau^2$.

The Gibbs sampler draws from conditional distributions of each of the parameters in θ, conditional on the last value of the other parameters. We use the notation $a|\theta_{-a}$ to denote the conditional distribution of parameter a, conditional on all other parameters.

1. Sample $\beta|\theta_{-\beta}$ from a Normal distribution

   $$\begin{aligned} p(\beta|\theta_{-\beta}) &\propto N(a, A), \\ A &= (B^{-1} + X'X)^{-1}, \\ a &= A(B^{-1}b + X'Z_\beta), \end{aligned}$$

   where the prior of β is $N(b, B)$, and $Z_\beta = Y^* - C\delta$. We use a diffuse prior with mean zero and variance of 1000.

2. Sample $\delta|\theta_{-\delta}$ from a Normal distribution

   $$\begin{aligned} p(\delta|\theta_{-\delta}) &\propto N(\hat{\delta}, \hat{\Delta}), \\ \hat{\Delta} &= (\Sigma^{-1} + C'C)^{-1}, \\ \hat{\delta} &= \hat{\Delta}(\Sigma^{-1}(Q\Gamma) + C'Z_\delta), \end{aligned}$$

where $Z_\delta = Y^* - X\beta$.

3. Sample y^*_{hvd} from a truncated Normal distribution, where truncation is to the positive side if $y_{hvd} = 1$, or negative side otherwise, from

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

4. Sample $\gamma|\theta_{-\gamma}$ from a Normal distribution

$$\begin{aligned} p(\gamma|\theta_{-\gamma}) &\propto N(g, G), \\ G &= ((I_D - \omega R)T^{-1} + Q'\Sigma^{-1}Q)^{-1}, \\ g &= G(Q'\Sigma^{-1}\delta). \end{aligned}$$

5. Sample $\omega|\theta_{-\omega}$

We use the Metropolis-Hastings algorithm to sample the spatial correlation parameter, ω, with autoregressive proposal density as follows: $q(\omega^t|\omega^c) = \omega^c + u$, where $u \sim N(0, \sigma^2)$, and σ^2 is a tuning parameter. The prior distribution of ω, denoted by $\pi(\omega)$, is uniform between the reciprocals of the highest and lowest eigenvalues of W (Sun et al. 1999). The new draw, ω^t is accepted with probability

$$\min\left\{1, \frac{f(\gamma|\Psi^t)\pi(\omega^t)q(\omega^c|\omega^t)}{f(\gamma|\Psi^c)\pi(\omega^c)q(\omega^t|\omega^c)}\right\},$$

where $f(\gamma|\Psi(\cdot))$ is the kernel of the distribution of γ conditional on $\Psi(\cdot)$ from level III of the model, and $\Psi = (I - \omega W)^{-1}$, where $W_{ij} = I(j \in R_i)$.

6. Sample $\sigma^2_d|\theta_{-\sigma_d}$ from an Inverse Gamma distribution

$$\begin{aligned} p(\sigma^2_d|\theta_{-\sigma^2}) &\propto IG(s_1, s_2), \\ s_1 &= (\sum_v I(v \in d) + \alpha_s)/2, \\ s_2 &= (\sum_v (\delta_{vd} - \gamma_d)^2 + \beta_s)/2, \end{aligned}$$

where the prior distribution of $\sigma_d^2 \sim IG(\alpha_s, \beta_s)$, $\alpha_s = \beta_s = 0.001$

7. Sample $\tau|\theta_{-\tau}$ from an Inverse Gamma distribution

$$\begin{aligned} p(\tau^2|\theta_{-\tau^2}) &\propto IG(t_1, t_2), \\ t_1 &= (D + \alpha_t)/2, \\ t_2 &= ((A\Gamma)' A\Gamma + \beta_t)/2, \end{aligned}$$

where $A = (I - \omega W)^{-1/2}$ and the prior distribution of $\tau^2 \sim IG(\alpha_t, \beta_t)$, $\alpha_t = \beta_t = 0.001$

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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 Organization, 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 Organization, Employment & Unemployment Schedule, Round 55.

Table 3: Description of Dependent and Explanatory Variables

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 attends 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 Organization, 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 Organization, 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 Organization, 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.

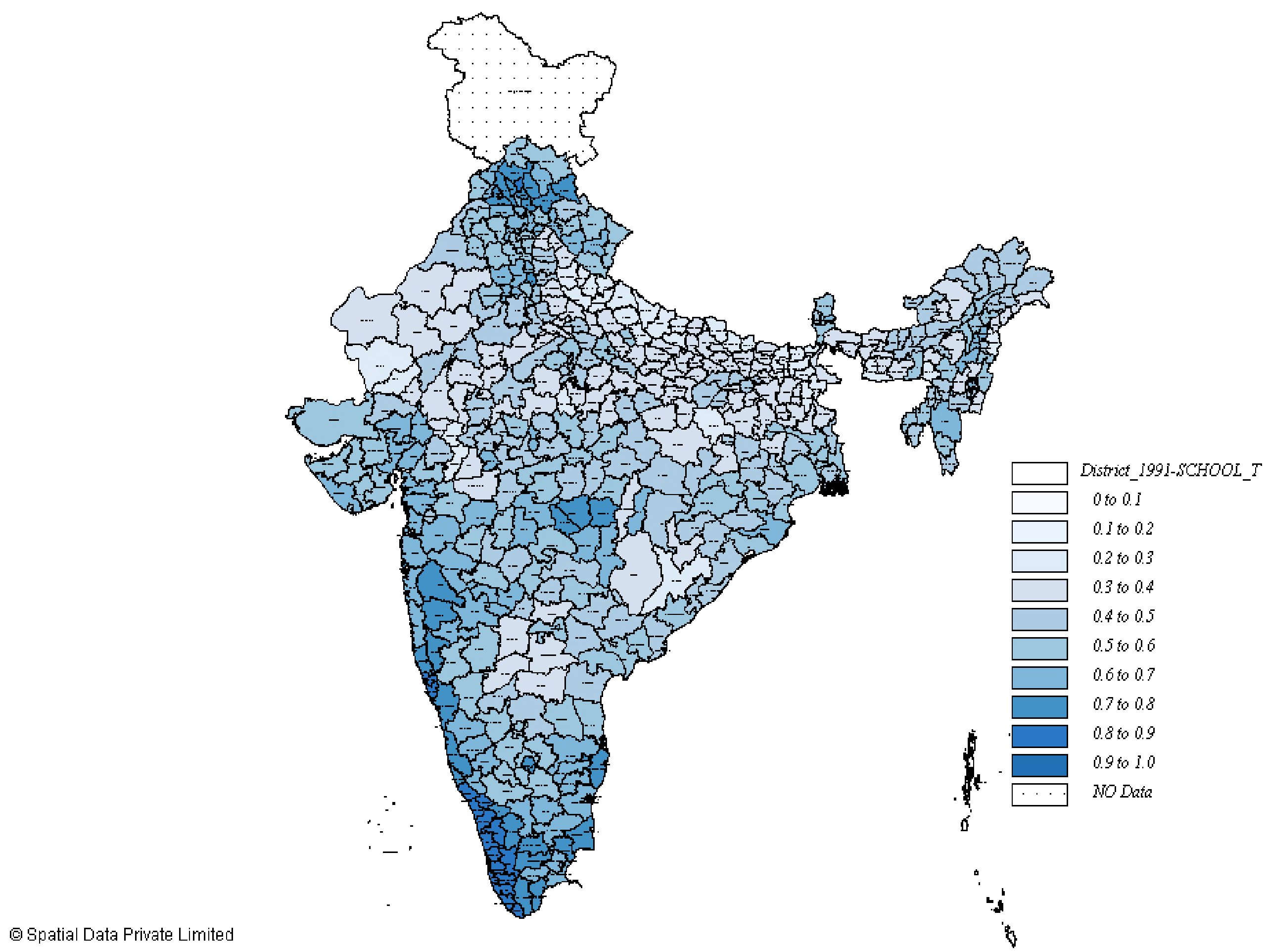

Figure 1: Proportion of Children Attending School: Indian Districts, 1991

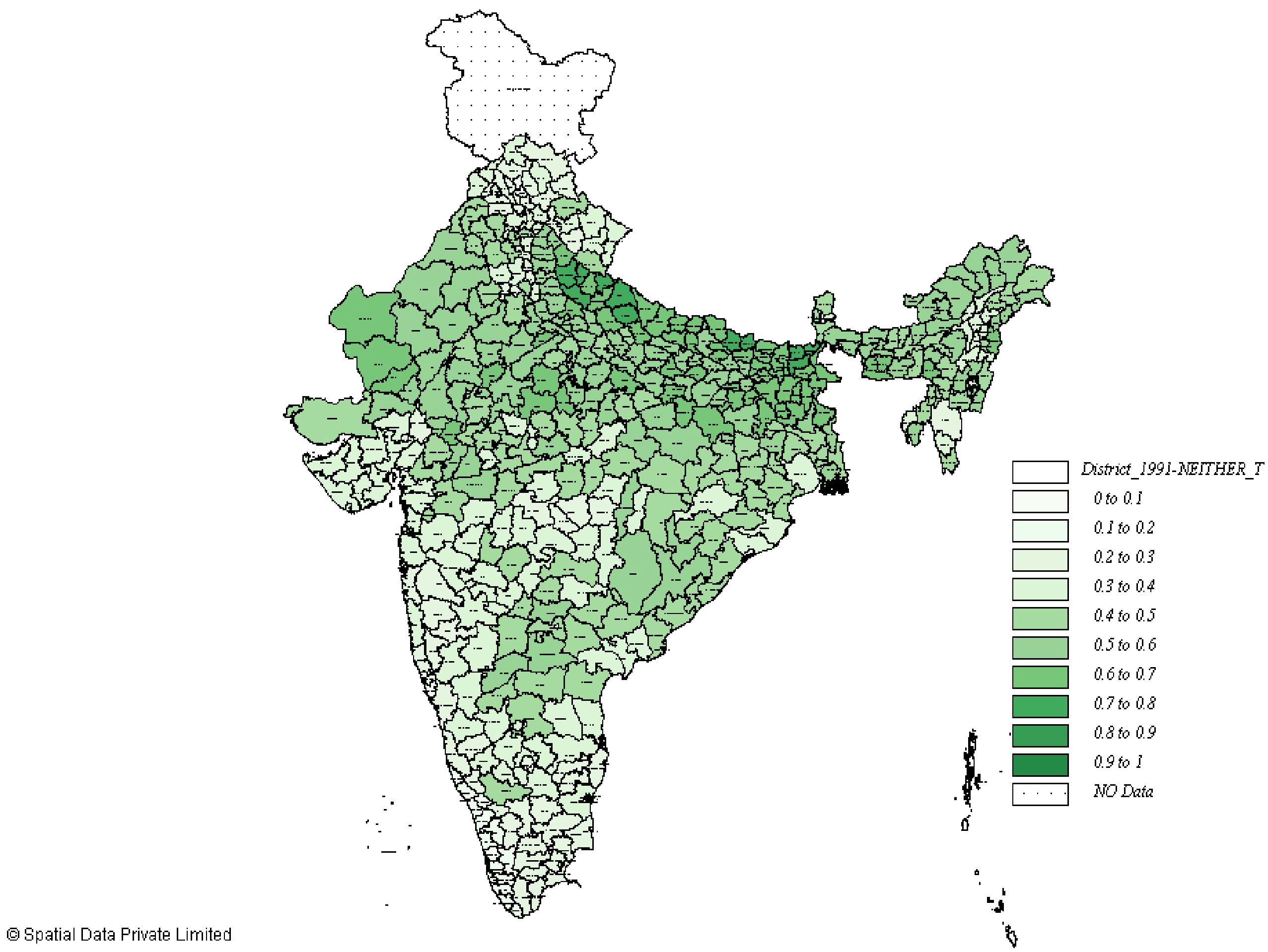

Figure 2: Proportion of Children Neither Attending School Nor Working: Indian Districts, 1991

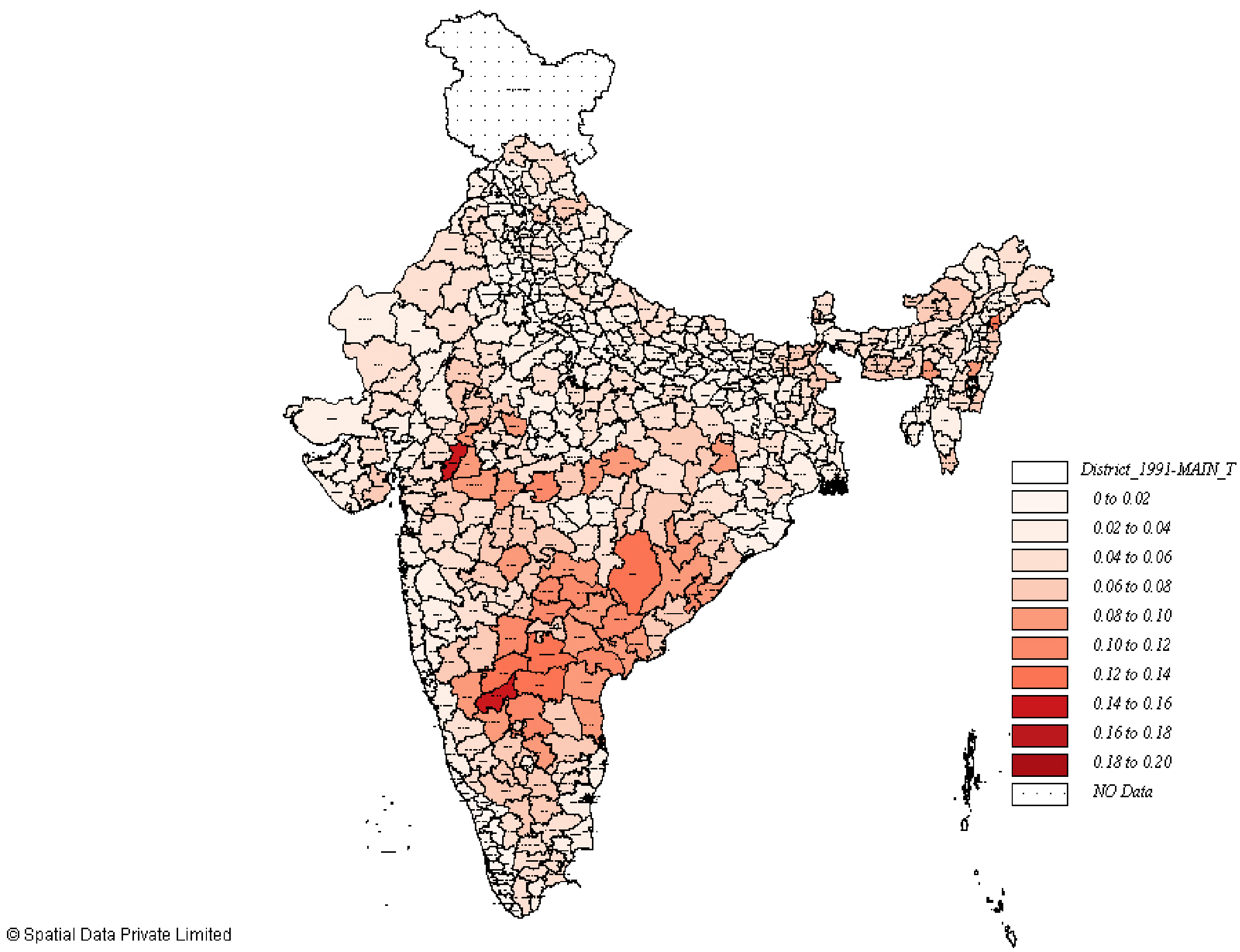

Figure 3: Proportion of Children Engaged in Child labor: Indian Districts, 1991

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	12.55	14.07	10.94	16.73	14.81	18.75
90	Kodagu	Karnataka	84.76	80.39	88.89	10.48	15.69	5.56
90	Chhindwara	Madhya Pradesh	49.43	47.00	52.63	21.02	23.00	18.42
90	Pali	Rajasthan	69.79	88.64	53.85	11.46	4.55	17.31
90	Dungarpur	Rajasthan	50.44	71.19	27.78	24.78	18.64	31.48
80	Idukki	Kerala	87.76	86.96	88.46	4.08	4.35	3.85
80	Vidisha	Madhya Pradesh	62.60	66.18	58.73	30.53	27.94	33.33
80	Cuttack, Jagatsinghpur	Orissa	80.65	85.39	76.29	16.85	14.61	18.90
80	Mongam	Sikkim	78.05	75.44	80.30	17.89	19.30	16.67
70	Shahdol	Madhya Pradesh	60.11	67.11	55.14	23.50	21.05	25.23
70	Chhimtuipui	Mizoram	53.55	59.26	47.30	40.00	34.57	45.95
70	Zunheboto	Nagaland	93.55	100.00	90.91	3.23	0.00	4.55
70	Nagaur	Rajasthan	64.09	77.87	46.94	21.82	14.75	30.61
70	Udaipur, Rajsamand	Rajasthan	69.25	78.73	59.02	17.84	14.03	21.95
70	Chittaurgarh	Rajasthan	71.94	83.33	59.70	17.27	9.72	25.37
60	Darrang, Sonitpur	Assam	64.60	70.55	57.33	21.20	17.82	25.33
60	Sitamarhi	Bihar	41.30	43.65	38.46	52.61	53.17	51.92
60	Bhavnagar	Gujarat	11.02	11.57	10.48	17.96	17.36	18.55
60	Sidhi	Madhya Pradesh	67.86	78.05	53.45	25.71	20.73	32.76
60	Lunglei	Mizoram	17.99	18.09	17.89	28.57	21.28	35.79
60	Wokha	Nagaland	97.22	100.00	94.12	2.78	0.00	5.88
60	Ajmer	Rajasthan	76.21	85.48	65.05	14.54	7.26	23.30
60	Kanniyaikumari	Tamil Nadu	94.57	96.23	92.31	2.17	1.89	2.56
60	Ballia	Uttar Pradesh	69.31	70.75	67.47	23.81	24.53	22.89
60	Haora	West Bengal	77.55	76.96	78.19	17.60	19.12	15.96

Source: National Sample Survey Organization, 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, according to the NSSO data.

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

Cutoff (%)	**District**	**State**	**Child Labor(%)**		
			All	Boys	Girls
90	Dharwad	Karnataka	8.65	7.35	10.00
90	Bolangir, Sonepur	Orissa	2.63	1.14	4.69
90	Chittaurgarh	Rajasthan	10.79	6.94	14.93
90	Gyalshing	Sikkim	2.68	1.40	4.24
90	Tiruchirappalli	Tamil Nadu	1.64	1.60	1.69
80	Dibang Valley	Arunachal Pradesh	1.52	1.25	1.92
80	Samastipur	Bihar	4.76	2.56	7.02
80	Ranchi	Bihar	4.32	2.53	6.02
80	Gandhinagar	Gujarat	9.52	5.00	13.64
80	Chhindwara	Madhya Pradesh	10.80	9.00	13.16
80	Bombay	Maharashtra	1.46	0.59	2.33
80	Osmanabad	Maharashtra	2.61	1.79	3.39
80	Latur	Maharashtra	4.42	3.70	5.08
80	Bhilwara	Rajasthan	18.01	16.05	20.00
70	Junagadh	Gujarat	5.59	1.74	10.00
70	Vadodara	Gujarat	9.64	5.60	13.71
70	Sirampur	Himachal Pradesh	1.65	0.00	3.23
70	Mandhya	Karnataka	5.65	4.62	6.78
70	East Nimar	Madhya Pradesh	1.74	1.03	2.67
70	Amravati	Maharashtra	1.74	1.09	2.50
70	Jaintia Hills	Meghalaya	4.05	6.45	2.33
70	Ganjam, Gajapati	Orissa	10.02	5.96	13.93
70	Pali	Rajasthan	18.75	6.82	28.85
70	Kota, Baran	Rajasthan	3.55	0.71	6.34
70	Basti, Sidharthanagar	Uttar Pradesh	13.46	5.22	22.22
70	Hooghly	West Bengal	6.30	2.97	10.06
60	Sibsagar, Golaghat, Jorhat	Assam	2.83	2.52	3.13
60	Bhind	Madhya Pradesh	2.50	0.00	6.25
60	Shajapur	Madhya Pradesh	15.60	4.92	29.17
60	Mandla	Madhya Pradesh	9.73	6.67	13.21
60	Bishnupur	Manipur	0.59	0.00	1.20
60	Cuttack, Jagatsinghpur	Orissa	2.33	0.00	4.47
60	Jaipur, Dausa	Rajasthan	5.29	1.14	9.94
60	North Arcot	Tamil Nadu	4.73	3.15	6.17
60	Azamgarh, Maunath Bhanjan	Uttar Pradesh	6.13	3.76	8.75
60	Jaunpur	Uttar Pradesh	4.42	2.22	6.92
60	Ballia	Uttar Pradesh	6.35	3.77	9.64

Source: National Sample Survey Organization, 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, according to the NSSO data.