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Agricultural Technology and Child Labor: Evidence from India

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Abstract

Child labor continues to be a major problem in developing countries, particularly in agricultural countries. The latest ILO global report points out that nine out of every ten child laborer is involved in the agricultural sector. The focus of this paper is on the rural sector in India, a country where child labor continues to be a major problem. A number of factors have been found to significantly influence the extent of child labor. This paper will focus on the type of technology utilized in the agricultural sector. Technology is divided into two types: biochemical and mechanical. The empirical results indicate that biochemical technology is not strongly linked to child labor. However, mechanical technology is found to have a statistically significant and negative impact on child labor.

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I. Introduction

Child labor is a significant problem in the world's economy. According to the International Labor Organization there are about 127 million children engaged in child labor in the Pacific and Asian regions alone. A large proportion of these children live in India. That is, 100 million of these child laborers live in India (Kurosaki, et. al., 2006). An in-depth look at the distribution of child labor reveals that this is a problem mainly in the rural sector of the economy. According to the Indian Embassy (http://www.indianembassy.org/policy/Child_Labor/childlabor.htm), "Children under fourteen constitute around 3.6% of the total labor force in India. Of these children, nine out of every ten work in their own rural family settings. Nearly 85% are engaged in traditional agricultural activities. Less than 9% work in manufacturing, services and repairs. Only about 0.8% work in factories." The Indian government has made attempts to deal with this problem. However, these attempts have not been very successful. The implication is that there must be some fundamental factors or circumstances which create conditions under which child labor thrives.

In order to determine what these factors might be, significant research at the microeconomic level is necessary. This paper will seek to pursue such research utilizing data drawn from a household survey for two Indian states carried out by the World Bank's Living Standards Measurement Study (LSMS) entitled "Survey of Living Conditions, Uttar Pradesh and Bihar, December 1997 - March 1998." The survey covers 2,250 rural households drawn from 120 villages selected from districts in southern and eastern Utter Pradesh and northern and central Bihar.

The basic assumption being made in this paper is that a household will not send children to work if their income is sufficiently high from non-child labor services. Additionally, it is assumed that adult labor and child labor are substitutable when agricultural technology is labor intensive, but not when technology is more advanced. The hypothesis being made in this paper is that when agricultural technology is more advanced it not only reduces/eliminates the need for child laborers, it also makes the agricultural sector more productive.

It has been argued in the literature that once technological progress takes place, adult and child labor become imperfect substitutes. Moreover, this stage, which is more productive and yields greater income, requires a greater degree of skill and knowledge. This increases the need and returns to education. Thus it makes education of children more lucrative for parents while making children redundant as laborers. This outcome is confirmed by Foster and Rosenzweig (1996) using data from the Green Revolution period in India. In addition, since adults are more productive it implies an increase in family earnings which eliminates poverty as a reason for sending children to work (Basu and Tzannatos, 2006). Thus, one can expect to find reduction in child labor when a country enters this stage of development in agriculture.

The main contribution of this paper is not just establishing the link between agricultural technology and child labor, but to examine the impact of different types of agricultural technology on child labor. Agricultural technology is generally divided into two types or varieties: biochemical and mechanical (Hayami and Ruttan, 1985). Biochemical technologies involve the use of high yield seeds, fertilizer, and irrigation. It allows for a more intensive cultivation of the land. Mechanical technologies utilize machinery to substitute for labor. Thus it results in a more extensive cultivation pattern.

The impact of these different types of technology on child labor is not so straightforward. Mechanical technologies are generally labor-saving in nature. Thus the application of such technology would likely reduce the employment of children. Biochemical technologies are more intensive systems of cultivation and will likely require a greater labor intensity in the production process. This might increase opportunities for child labor and thus lead to more of such activities by children. However, the successful application of biochemical technologies requires a careful and precise application of water and fertilizer at appropriate times. Thus the labor required will need to be more skilled. An alternative way of thinking about this is to view the use of this technology as requiring a number of informed decisions that require experience and knowledge in terms of allocation of resources. Child labor is not likely to be effective in the application of a sophisticated technological package. The return to education for children will increase thus resulting in parents deciding to send their children to school.

This issue will be the focus of the paper. The next section will briefly review the literature on child labor. Section III will discuss the data as well as the empirical methodology that will be used. Section IV will present and discuss the results. The last section will summarize the paper and draw conclusions.

II. Review of Literature

The first difficulty that faces those seeking to do research on child labor is one of definition. What is a child and what will be counted as labor? The ILO defines child labor as follows. For ages 5-11, it is treated as synonymous with economically active. Economically active is any child who did one hour or more of work in the previous week. For ages 12-14, the definition includes children who do 14 hours or more of non-hazardous work per week or one hour or more of hazardous work per week (Basu and Tzannatos, 2006).

In addition, there are two types of work. The first includes labor for which the child is paid a wage and usually involves working for someone outside the family. The second type of work is unpaid, not for market work that is usually done in the household. If one includes as labor only market work, the work of female children will be underestimated since they do a large proportion of the work in the household (Basu and Tzannatos, 2006).

In this paper, the broader definition of child labor will be used, including market and non-market (household) labor. However, in terms of age the analysis will be restricted to those aged 10 through 14. This is due to the fact that the data survey utilized gathers information about the work activities of only those above the age of 10.

As to the causes of child labor, the most often discussed factor is family poverty. The analysis here is usually based on two assumptions: the luxury axiom and the substitutability axiom. The first implies that child schooling and leisure activities (child non-work activities) are luxury goods. With luxury goods the proportion of ones income devoted to such activities rises with the level of income and vice versa. The second presumes that adult and child labor are substitutes subject to some adult equivalency correction (Basu, 1999).

The assumptions create a particular perspective with respect to the labor market. The demand for labor is inversely related to wage, a typical demand for labor curve. At a high enough wage no child labor will occur and the potential supply of labor is limited to adult labor. As wages decline, the supply of labor is augmented by child workers. In other words, the supply of labor is backward sloping (Basu, 1999).

In the conditions discussed above, some interesting possibilities emerge. The first is that multiple equilibria are possible. The demand may intersect supply at two points, a low wage equilibrium with child labor and a high wage equilibrium with no child labor. In this case a country could be stuck in the low wage equilibrium and government policy could eliminate the child labor by coordinating the shift from the low to high wage equilibrium. Reform would be relatively effective. Alternatively, the demand for labor may be so low such that the only equilibrium which exists is the low wage equilibrium. In this case, government reform via coordination cannot succeed. Poverty has led to child labor (Basu, 1999).

Child labor is also likely related to the availability of schools and education. In a situation in which taxes are low and there are few schools, most children will work. Rising taxes devoted to improving schools and providing greater school availability is likely to induce families to send their children to school rather than work. Related to this, if schools provide lunch and other amenities to students and/or their families, this is also likely to lead to families deciding to send their children to school rather than work (Tanaka, 2003).

The education levels of the parents are also likely to be an extremely important determinant of child labor. Parents that already possess some level of education are likely to be more cognizant of the positive role which education can play in the future of their children. Thus, they will likely choose to send their children to school rather than work. An interesting question concerns whose education is likely to be more important. It is now commonly accepted that “one smart way to fight poverty is to empower women (by educating girls, by giving daughters legal rights to inheritance, by promoting banking institutions that give women control over the accounts). Once mothers control family spending rather than fathers, family resources are invested more productively, and some families can rise out of poverty very quickly” (Kristof, 2007). Thus one might hypothesize that the education of the mother has a more important effect on child labor.

As discussed earlier, this paper also hypothesizes that the type of agricultural technology utilized also has an impact on the extent of child labor. Mechanical technologies substitute mechanical power for labor leading to extensive farming. It is hypothesized that this reduces the need for child labor. Also the operation of machinery is likely to require experience and skill which many children will lack. The alternative technology is biochemical and it intensifies the production process. There are two hypothesized effects here. First, the utilization of this technology is likely to increase the demand for labor, thus providing additional opportunities for child labor. However, the labor utilized must be able to make informed decisions concerning the use of a sophisticated technology. This would likely exclude most child laborers. In addition, the family’s experience with using a sophisticated technical package is likely to convince them of the high return to additional education for their children.

The variables discussed above will be incorporated in the empirical analysis of the next section. It is to this section that we now turn.

III. Data and Empirical Model

As stated earlier, the data utilized in this paper is drawn from the World Bank's Living Standards Measurement Study (LSMS), the Survey of Living Conditions, Uttar Pradesh and Bihar, December 1997-March 1998. The sample includes 2,250 households. Because this paper concentrates on households which earn their living in agriculture, the data set utilized is a little over 1,000 households. Again the focus is on those children aged 10-14 because the survey only provides work information on those aged 10 or above. Henceforth the term children will be assumed to refer to this age group. Work is defined to include both market and non-market (household activities) in this study. Since this paper utilizes a binomial logit model, children are simply divided into those who work and those who do not. The data set and approach utilized here are very similar to that in Sakamoto (2006). However, our focus is on farming households and on analyzing the impact of agricultural technology on child labor.

There are a total of 1,566 children aged 10 to 14 that belong to households that are primarily agricultural. These are families where the person who is the main breadwinner for the family works solely in the agricultural sector and over 50% of the household's income comes from the agricultural sector. Of these 1,566 children, parents of 1,455 children respond to the questions regarding work. The rest simply do not respond. Of those that respond about 30% of children are reported as working. The reader should be aware that this is most likely under-reported given that it is parents who are answering the questionnaire. When asked about how many hours children work about 90% do not respond. Of those that do, the hours range from a few hours a week to fifty hours a week. However the number of no responses to hours shows that parents are probably reluctant to reveal this information to the interviewer. However, the analysis is based on the available data.

In terms of some individual characteristics of the children in the sample, while the total sample of children has about an even distribution by gender, it is quite different when considering only those that also work. Of those children, 70% are female and 30% are male. Thus, at the very onset it seems quite apparent that more girls are sent to work than boys. In terms of the ranking or birth order of children, the sample reveals that about 21% are first born or the oldest among their siblings. However among only those that work about 30% are the oldest sibling. Thus there seems to be a higher likelihood of a child being sent to work being the oldest.

Among household characteristics, we have looked at the education level of the children's parents as well as household size. The average education level of a father is 3.04 (where according to the ranking system in the survey design 3 means less than primary and 4 equals primary level education). The average education level of a mother is 1.4 (where 1 is illiterate and 2 is literate, but without any formal schooling). In terms if being literate or not, the data shows that for the overall sample of children about 47% of them have father's who are illiterate while 73% have mothers that are illiterate. However among the children that are sent to work about 66% have illiterate fathers and 84% have illiterate mothers. It is interesting to note that among all children about 27% are illiterate, but among those that work 71% are illiterate. Thus the data seems to indicate that a child that is sent to work is much more likely to be kept from going to school. This particular data set does not appear to provide much support for the complementarity between schooling and child labor. In terms of household size, the average household has a little over 8 individuals in it with the lowest number being 2 and the highest 29. However when we reexamine the data for only those children that work, we find that on average the family size of those that work is marginally smaller (7.56) than for those that do not work (8.65).

Some other aspects of household characteristics that are looked at include religion and caste. With reference to religion the data shows that about 90% of all children in the sample are from Hindu families. This distribution remains fairly consistent when we look only at those that work. The only other religion is Muslim and they are clearly a minority. However, when we look at the distribution of children by household caste the distribution shows discrepancies between the entire sample and the sample of only those that work. Out of all children in the sample about 21% belong to middle and upper caste while about 79% belong to the lower caste. However, when we look at the caste distribution of only those that work we find that only about 9% of those children belong to middle and upper caste while 91% belong to the lower caste. Here again, it seems that the distribution is skewed towards lower caste when it comes to those that send their children to work.

Next we turn our attention to the economic condition of families with children. Out of all children in the sample about 33% belong to families that fall under the poverty line. However among only those children that work, a little more than 44% belong to families under the poverty line. Thus it shows that children are seen as a means of additional income and therefore children of poorer families are more likely to be sent to work. One of the questions that families are asked is whether or not they get two square meals a day. To this, about 93% respond in the affirmative. This number falls slightly (89%) for the sample of children that work. Thus, for the most part, most of the families have adequate food. Another way of measuring the economic status is by looking at the wealth of a household. For this we look at how many children belong to families that are landowners. About 94% of all children that belong to agricultural families are also families that own land with the average age owned being about 3.08 s. This number does not change much for the sample of children that work. Here it is seen that about 92% belong to families that own land. However the average age owned by families where children work is relatively smaller (2.43) than for those who do not work (3.37).

Next the focus turns to the extent of indebtedness of families. In terms of the amount of loans received net of loans made (indebted position of the family), the data shows that about 94% of families are in debt with the average amount of debt per child being about four thousand rupees. This implies that only about 6% of children are in families that are net creditors. Given that a majority of families are very poor, this seems to be very large amount of debt. For the narrower sample of children that work the number of families in debt rises to 95%, a marginal difference, with the average amount of debt being about a four and a half thousand rupees per child.

The variables of interest for this paper are the different types of agricultural technology in use. Three different farming technologies are found to exist and are studied. These are how much fertilizer is utilized per acre of cultivated land, total farm assets/implements per acre of cultivated land, and how much of the cultivated land gets irrigated. In terms of fertilizer use, about 83% of children belong in families that use some form of fertilizer on their land. The average money value of fertilizer use is a little over Rupees 215. Among children that work about 73% belong to families that use some fertilizer. The average amount spent on fertilizers for these families is about Rupees 206.

In terms of ownership of some form of farm asset, about 55% of children belong to families that own some assets. Among those children that work, about 46% belong in families that own some farm assets. These assets include tractor, ploughing implements, cart, thresher, trolley, fodder cutting machine, and generator. On average the families spend about Rupees 9,550 on farm assets. For those children that work, the average amount spent of farm assets is considerably lower at Rupees 3,485. In terms of irrigation, about 96% of children belong in families that undertake some amount of artificial irrigation for their land. The average portion of land irrigated stands at about 65%. The share of families that irrigates their land is pretty consistent between the larger sample of children and of those that work. However the average portion of land irrigated for this smaller sample stands at around 52%. This may be relatively small compared to the larger sample, but it shows that families are willing to spend their money (which is mostly borrowed) to irrigate their land, invest in farm assets and spend on fertilizers to help with the productions process.

Finally, the attention is turned towards some village specific information that is likely to affect parents' decisions about sending children to work. These are dummy variables to account for the presence of a middle school and a secondary school in the village. Given the age group of children being studied, a primary school is likely to be irrelevant. The data shows that for the entire sample of children about 26% live in villages that have a middle school and about 9% have a secondary school. These numbers are pretty consistent between the larger sample of all children and only those that work. These low numbers, along with some of the other characteristics discussed above, probably account for the high percentage of illiteracy found among the children.

Now that the reader has some idea about some of the characteristics of the variables being utilized in the paper, our attention turn to the model being used to carry out the analysis. A binomial logit model is utilized for the analysis which is specified as:

$$P(y_i = 1|x_i, \beta) = 1 - (e^{-x_i'\beta}/(1 + e^{-x_i'\beta}))$$
$$= e^{-x_i'\beta}/(1 + e^{-x_i'\beta})), \qquad (1)$$

which is based upon the cumulative distribution function for the logistic distribution. The choice of whether or not to send a child to work is denoted by y while x denotes the vector of regressors that explains y. The dependent variable y takes the value 1 if a child works and 0 otherwise. Based on the above, the regression that is estimated for the empirical analysis is given by

$$W_{ijk} = \alpha + \beta_1 \textit{ Individual} + \beta_2 \textit{ Household} + \beta_3 \textit{ Village} + \beta_4 \textit{Agtech} + \varepsilon_i, \qquad (2)$$

where W_{ijk} is a zero, one variable representing whether child i in household j and village k works or not. *Individual*, *Household*, and *Village* are vectors of characteristics of child i, household j, and village k. The variable *Agtech* represents the vector of agricultural technology variables. The β's are the parameters to be estimated.

The individual characteristics include the following variables. First, it is of interest to know whether female or male children are more prone to work. Thus a dummy variable is utilized for male (*Male*). It also seems that first born children are thought to be more likely to work, since they are often put in charge of household activities in particular. Thus a dummy variable for oldest child is also utilized (*Oldest*).

A number of household variables are also included. As argued previously, the education of the parents is likely to be important and it is of interest to know whose education matters. Thus variables for head of family's education (*Headedu*) and mom's education (*Momedu*) are included, both of which measure of level of education achieved in terms of years. Household size measured in terms of the number of members (*Hhsize*) is also a right-hand side variable. The impact on child labor could be either positive or negative. The larger family needs more resources to survive, thus it may require additional child labor. Alternatively, the larger the extended family (income earners), the less the need for children to work.

India is characterized by a caste type status system. One inherits at birth one's caste. Upper caste families, high social status, are more likely to send their children to school. Castes are measured by a dummy variable which is one if the household is an upper or middle caste, zero if lower or tribal (*Hhcaste*). There are two main religions in the study area, thus a dummy variable for Hindu is incorporated (*Hinduhh*).

One of the main hypotheses in the literature argues that poverty and child labor are linked. The measure of poverty utilized incorporates two types of data drawn from the household sample. A household is defined to be poor if they are below the poverty line or they had insufficient food (*Poor*). A household below the poverty line "qualifies for the Below Poverty Line (BPL) subsidy for food grains offered through the revamped Public Distribution System (PDS)" (Sakamoto, 2006). Insufficient food occurs if the household did not get at least two "square meals" a day. If one or the other is true for a particular family, that family is classified as poor.

The extent of indebtedness of a family is also thought to influence the extent of child labor. The more debt, the greater the extent to which children must work. This is measured by the variable net loans (*Netloan*) which measures the amount of loans received net of loans made. The wealth of a household is also likely to influence the decision to send children to work. The wealthier the household, the less likely children will be sent to work. Wealth in agriculture is mainly related to land ownership. Thus a dummy variable which is one if some land is owned and zero if otherwise (*Landowner*) is added to the estimating equation.

Finally, measures of agricultural technologies utilized by each household are also incorporated. There are three variables involved. The first is the ratio of fertilizer (kilograms) to acres of cultivated land (*Agtech1*). The second is the ratio of mechanical implements (measured in Rupees) per acre of cultivated land (*Agtech2*). The third is the percent of cultivated land that is irrigated (*Agtech3*). These will be combined in several ways so as to represent the two types of agricultural technology.

In terms of village variables, the availability of schools at particular levels is also utilized as right-hand side variables. Thus a dummy variable indicating the presence of a middle school or not (*Villmid*) in the village and a dummy variable indicating the presence of a secondary school in the village are utilized. The idea is that if such schools are available, children are more likely to go to school. The reader will note that there is no variable representing the availability of a primary school in the village. This is due to the fact that only children 10 to 14 make up the sample. For the most part, the availability of primary school is likely to be irrelevant.

The next section of the paper will present the empirical results and interpret them. Following this will be a summary and conclusions.

IV. Empirical Estimation

The main purpose of this paper is to examine the impact of two types of agricultural technology, mechanical and biochemical, on child labor. There are three variables, discussed in the previous section that are of interest; fertilizer use per acre (*Agtech1*), mechanical inputs per acre (*Agtech2*), and irrigation as a percentage of cultivated land (*Agtech3*). Although the estimations below will include these three measures, they will also be combined to better represent the characteristics of biochemical and mechanical technology. Specifically, biochemical technology will be represented by an interaction term created by multiplying the fertilizer per acre variable by the irrigation variable (*Agtech1·Agtech3* = *Agtech4*). The mechanical technology is, of course, represented by *Agtech 2*.

Before presenting regression results, we present some selected summary statistics in Tables 1 and 2. Table 1 summary statistics correspond to the entire sample of children while the summary statistics in Table 2 correspond with the narrower sample consisting of only those children that work. Binary variables have been left out of the summary statistics.

The results of the first set of estimations are presented in Table 3. The first column (3.1) represents the estimation including the three technology variables (*Agtech1*, *Agtech2*, and *Agtech*3). The second column (3.2) represents the results of the estimation including two technology variables, *Agtech1·Agtech3 = Agtech4* and *Agtech2*. The first thing to see is the gender bias involved in child labor. The sign on the male dummy variable is negative, statistically significant, and the coefficient is large. Thus males do significantly less labor relative to females. In addition, the oldest child variable is positive and significant implying that the older children do more labor relative to their younger siblings. Also family size (*Hhsize*) has a significant negative impact.

In terms of education, both the head of family (*Headedu*) and mother's education (*Momedu*) are statistically significant and negative. Thus their education reduces the extent of child labor. Examining the relative size of the coefficients, mother's education is larger relative to head of household. Thus the mother's education would seem to be particularly important in reducing child labor. In terms of the availability of schools, the availability of middle schools (*Villmid*) has a statistically signature negative impact, but secondary school (*Villsec*) availability is not statistically significant.

In terms of social variables, it seems that the religion of households has no significant impact. However, caste seems to be important. The measure is a dummy variable becoming one if the caste is upper or middle and zero if it is lower or tribal (*Hhcaste*). As one can see, higher caste families are associated with less child labor.

There are three variables related to the economic status of the family. First, the dummy variable determining whether the family is poor or not (*Poor*) is positive, but it is not statistically significant. More will be said later concerning this variable. The extent of indebtedness, measured as *Netloan*, also has a positive sign and is statistically significant. Finally, the landowership (*Landowner*) is negative in its impact, but it is not statistically significant.

With respect to the agricultural technology variables, several interesting results emerge. First, when all three are included (first column), *Agtech2* (mechanical inputs per acre) and *Agtech3* (percentage of cultivated land that is irrigated) are both negative and statistically significant. When the interaction term for biochemical technology is used (*Agtech1·Agtech3 = Agtech4*), it is not statistically significant. However, the mechanical technology variable (*Agtech2*) continues to be negative and statistically significant. Thus mechanical technologies are associated with less child labor.

The last two columns of the table (3.3 and 3.4) report the results of interacting the landowership variable (*Landower*) with each of the technology variables. It may be that landowners are more likely to introduce these technologies. Thus *Agtech11*, *Agtech22*, *Agtech33* and *Agtech44* are all interaction terms calculated by multiplying the respective technology variables by *Landowner*. As one can see, most of the results are the same as those presented in columns one and two. However, in column three the poverty variable (*Poor*) is now significant and positive implying an association between poverty and child labor. As one can see in column three, the mechanical (*Agtech22*) and irrigation (*Agtech33*) technologies continue to have significant and negative association with child labor. Column four indicates, as did column two, that mechanical technology (*Agtech22*) has a significant negative on child labor while the biochemical technology variable (*Agtech44*) is not significant.

Now that the signs and significance of the variables have been discussed, attention is turned to the magnitude of the estimated coefficients. These are presented by the marginal probabilities of the variables and presented in Tables 3.1, 3.2, 3.3, and 3.4 where the table numbers correspond to the equation number given in Table 3. These show, for instance in Table 3.1, that if a child is male the chances of him being sent to work is 28% less than if the child was female. Additionally, the oldest child is 10% more likely than his or her younger siblings to be sent to work. A child going to middle school is 7% less likely to be sent to work, though being in secondary school has no significant influence on the decision to work. Interestingly enough the father's education level reduces the probability of a child working by 2% but mother education reduces it by double of that. Unfortunately, in our sample it is seen that the percentage of mothers that are illiterate is considerably higher than fathers. The results show that the caste status of a child has an important influence on work decisions. A child from middle to upper caste is 9% less likely to work compared to a child from a lower caste. It is interesting to note that the size of the household given by the *hhsize* variable has a significant negative impact on child labor. According to Table 3.1, there is close to a one to one relationship between the variables. That is, a one percent increase in the size of the household is likely to reduce a child from working by about 1%. The *poor* variable has a very small coefficient in equation 3.1 though it has a larger value in 3.2, 3.3 and 3.4, it is not statistically significant in any of these equations. Similarly the coefficient for the *Netloan* variable, though statistically significant, is quite small in all four equations. Finally, we turn to the agricultural technology variables which, for the purposes of this paper, are of utmost interest. The marginal probabilities show that according to equation 3.1, *agtech2* and *agtech3* will have statistically significant impact and reduce the probability of a child working by .001% and .03%. According to Table 3.2, *agtech2* will reduce the probability of child labor by .002%. In Tables 3.3 and 3.4 the agricultural technology variables are interaction terms as explained earlier. These show that *agtech22* and *agtech33* are both statistically significant in Table 3.3 and they will reduce the probability of child labor by .002% and .04% respectively. In Table 3.4, only *agtech22* is statistically significant and its coefficient value is similar to that in Table 3.3.

The results discussed above indicate that for all but one estimation, the *poverty* variable is not significant. The *landowner* variable is also not significant. This may be the result of multicollinearity between our measures of income and wealth (*Poor* and *Landowner*) and several other variables (*Villmid, Villsec, Momedu* and *Headedu*). This may have distorted the results of the estimations. Finding appropriate instrumental variables (for poverty or wealth) that could be used is quite difficult. In an attempt to deal with this problem, the sample is divided into two subsets, poor and not poor. Then equation (2) is reestimated, with some modifications, for each subset. The results will be analyzed to see if there are any dramatic changes in the results. This will sharply reduce the variation in income. A second approach will be to split the sample into those children living in households owning less than one acre of land and those with more than one acre of land. This will sharply reduce the variability of wealth and once again the results can be examined to see if there are dramatic changes in coefficient signs and significance levels. These results are presented in tables 4.1, 4.2, 5.1, and 5.2.

Tables 4.1 and 4.2 pertain to estimations for subsets of children in families below and above the poverty line. Examining the results for children in families below the poverty line (4.1), the first column separates agricultural technology into three parts: fertilizer intensity (*Agtech 1*), expenditures on mechanical implements per acre (*Agtech 2*), and proportion of cultivated land irrigated (*Agtech 3*). The second column multiplies the technology variables by the land ownership variable. The third and fourth columns use the mechanical (*Agtech 2*) and biochemical (*Agtech 4*) technology classification system with the fourth column interacting each technology term with the landownership variable.

The results indicate some substantial differences between the results for the full sample (Table 3) and the results for the subsets (Table 4,1 and 4.2). First the mothers and head of family's education ceases to be significant for those under the poverty line. However, they both become statistically significant for those above the poverty line. This suggests that higher income is likely associated with higher education of the parents which in turn influences child labor negatively. A second major difference is that the availability of a village secondary school is statistically significant and positive in its effect on child labor for those below the poverty line. This indicates the availability of a secondary school and child labor are complementary. However, the availability of either is unimportant for those above the poverty line. Finally, for the poor, agricultural technologies have no impact on child labor. However, for those above the poverty line mechanical and irrigation technologies have a significant negative impact on child labor. When technology is classified into biochemical and mechanical, only the latter is negative and statistically significant. The implication would seem to be that those with higher incomes can utilize these technologies which in turn have an impact on child labor.

As an alternative to the above procedure, the sample was divided into those whose family's owned one acre or less of land and those who owned more than one acre. If landownership is a measure of wealth, then the former group is less wealthy than the latter. These results are presented in Tables 5.1 and 5.2.

Again there are some significant differences with the results presented in Table 3. First, the head of household's education is not statistically significant in Table 5.1, but becomes statistically significant in Table 5.2. Thus wealthier households are characterized by more educated heads and this reduces child labor. However, female education is significant in both less wealthy and more wealthy households and the size of the coefficient continues to exceed that for head of household. Landownership is included in the regressions in Table 5.1 (Landowner is 1 if land is owned and 0 if it is not) and it is statistically significant and negative. It is not included in the estimations for Table 5.2 since all households in this subset own land.

The agricultural technology variables, for the most part, are not statistically significant for the less wealthy group. However, for the wealthier group *Agtech 2* and *Agtech 3* are statistically significant and negative, while *Agtech 1* is statistically significant and positive in its impact on child labor. These technology variables are not interacted with landownership (there are no *Agtech 11, Agtech 22, Agtech 33,* and *Agtech 44* variables) for the wealthy group, since all households in this group own land. When technologies are classified into mechanical (*Agtech 2*) and biochemical (*Agtech 4*), it is only the mechanical technology that is significant and negative. The biochemical technology variable is no longer significant (effects of fertilizer and irrigation intensity affect each other). The implication here seems to be that wealthier families can afford to utilize technology with mechanical technologies having a negative impact and biochemical technologies having no net effect on child labor.

V. Summary and Conclusions

The main focus of this paper has been on estimating the impact of different types of agricultural technology on child labor. Agricultural technology was divided into two varieties: biochemical and mechanical. Biochemical technologies generally utilize fertilizer, irrigation, and new seed varieties. The application of the technology intensifies the production process and it was hypothesized that it would increase the demand for labor, but this would be skilled labor (not likely child labor). It might actually induce parents to send their children to school rather than work, since parents using this technology are more likely to appreciate the benefits of education. The empirical results indicate that there is no relationship between the two.

The second type of agricultural technology is mechanical in nature. It substitutes machine energy for human energy, it is labor saving. It was hypothesized to have a negative effect on child labor. Indeed, the results do support this conclusion.

A number of interesting results emerge. First, male children are much less likely to be involved in child labor. The education of the parents is also an important factor in reducing child labor, but for the most part this holds for those above the poverty line and for those who have more wealth. Although, when wealth is utilized to divide the sample female education has a strong negative impact in both less and more wealthy households. Also, it is mother's education which is more important in terms of size of coefficient. Overall, higher income and wealthier households have better educated parents and thus less child labor (especially if the mother is educated).

As to agricultural technology, the main implication is that mechanical technologies reduce the incidence of child labor, whereas biochemical technologies are neutral in their impact. However, this impact would seem to be strongly related to income and wealth. That is, wealthier and higher income families have access to technology and the utilization of mechanical technology reduces child labor. Lower income, less wealthier households do not have access to the technology and they have no impact on child labor.

The results of this paper have important implications for policy related to demand for child labor. The results show that as an economy develops and people in the agricultural sector adopt more capital intensive technology, it reduces the demand for labor and makes adult and child labor imperfect substitutes. Both of these factors reduce the demand for child labor. Additionally, if economic development in the country side leads to better education opportunities, especially for women and children and improves the economic condition of families, they collectively lead to a reduction in the need for child labor and are therefore more likely to succeed in reducing this problem.

Table 1: Selected Summary Statistics for all children aged 10 – 14 in the sample

Variable		Obs	Mean	Std. Dev.	Min	Max
hhsize		1566	8.289911	4.072693	2	29
netloan		1517	3959.991	14258.79	-150000	170000
poorloan		1566	1198.55	4324.154	-2000	53000
agtech1		1182	10.48716	26.93388	0	416.6667
agtech2		1243	1452.529	4397.692	0	55705.77
agtech3		1243	54.98136	113.4374	0	1250
agtech4		1182	1578.763	13961.39	0	312500
agtech11		1182	10.06177	26.40573	0	416.6667
agtech22		1243	1442.924	4398.25	0	55705.77
agtech33		1243	52.13134	111.9882	0	1250
agtech44		1182	1564.956	13960.82	0	312500

Table 2: Selected Summary Statistics for only children that work

hhsize |	431	7.563805	3.210446	2	27
netloan |	413	4456.223	13316.65	-4000	170000
poorloan |	431	1273.457	3268.644	-2000	26200
agtech1 |	282	11.42319	24.65057	0	250
agtech2 |	305	597.7123	1920.943	0	28409.09
agtech3 |	305	52.2325	106.1272	0	1250
agtech11 |	282	10.6433	23.51871	0	250
agtech22 |	305	584.3324	1918.959	0	28409.09
agtech33 |	305	46.36353	100.5697	0	1250
agtech44 |	282	1788.467	18708.76	0	312500

Table 3

Variable	(3.1)[1]	(3.2)[1]	(3.3)[1]	(3.4)[1]
Male	-1.78 (-10.69)***	-1.76 (-10.65)***	-1.76 (-10.67)***	-1.74 (-10.60)***
Oldest	0.60 (2.72)***	0.54 (2.51)***	0.59 (2.64)***	2.52 (2.44)***
Headedu	-0.15 (-3.57)***	-0.14 (-3.40)***	-0.15 (-3.64)***	-0.15 (-3.55)***
Momedu	-0.29 (-3.28)***	-0.27 (-3.13)***	-0.29 (-3.32)***	-0.27 (-3.17)***
Hhsize	-0.07 (-3.11)***	-0.06 (-2.87)***	-0.07 (-3.24)***	-0.06 (-2.96)***
Hinduhh	-0.33 (-1.18)	-0.31 (-1.15)	-0.34 (-1.19)	-0.32 (-1.16)
Hhcaste	-0.71 (-2.87)***	-0.72 (-2.88)***	-0.72 (-2.91)***	-0.72 (-2.91)***
Poor	0.27 (1.52)	0.17 (0.95)	0.31 (1.73)*	0.20 (1.15)
Villmid	-0.57 (-2.64)***	-0.53 (-2.52)***	-0.54 (-2.55)***	-0.50 (-2.39)**
Villsec	0.30 (0.76)	0.32 (0.81)	0.29 (0.74)	0.30 (0.75)
Netloan	0.00001 (2.52)***	0.00001 (2.68)***	0.00001 (2.51)***	0.00001 (2.71)***
Landowner	-0.45 (-1.48)	-0.48 (-1.57)		
Agtech1	0.0002 (0.05)			
Agtech2	-0.0001 (-2.49)***	-0.0001 (-2.58)***		
Agtech3	-0.002 (-2.25)**			
Agtech4		-0.00004 (-0.80)		
Agtech11			0.0003 (0.11)	
Agtech22			-0.0001 (-2.46)***	-0.0002 (-2.58)***
Agtech33			-0.003 (-2.19)**	
Agtech44				-0.00005 (-0.84)
Pseudo R^2	0.20	0.20	0.21	0.20
N	1083	1083	1083	1083

1. The number in parentheses represents the z value with * representing significance at 10%, ** 5%, *** 1%.

Table 3.1: Marginal probabilities corresponding to equation 3.1

variable |	dy/dx	Std. Err.	z	P>|z|
male*|	-.2850301	.0271	-10.52	0.000
oldest*|	.1005709	.0417	2.41	0.016
headedu |	-.022085	.00623	-3.55	0.000
momedu |	-.0429965	.01282	-3.35	0.001
hhsize |	-.0099232	.00314	-3.16	0.002
Hinduhh*|	-.0529237	.04961	-1.07	0.286
hhcaste*|	-.0916147	.02865	-3.20	0.001
poor*|	.0415425	.02918	1.42	0.155
villmid*|	-.0743961	.02674	-2.78	0.005
villsec*|	.043909	.06853	0.64	0.522
netloan |	1.65e-06	.00000	2.58	0.010
landowner*|	-.0855499	.05822	-1.47	0.142
agtech1 |	.0000307	.00043	0.07	0.943
agtech2 |	-.0000193	.00001	-2.61	0.009
agtech3 |	-.0003391	.00015	-2.25	0.025

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Table 3.2: Marginal probabilities corresponding to equation 3.2

variable |	dy/dx	Std. Err.	z	P>|z|
male*|	-.2825138	.02697	-10.48	0.000
oldest*|	.0888954	.0397	2.24	0.025
headedu |	-.0214965	.00622	-3.46	0.001
momedu |	-.0412588	.01291	-3.19	0.001
hhsize |	-.0090768	.00311	-2.92	0.004
Hinduhh*|	-.0502055	.04813	-1.04	0.297
hhcaste*|	-.0925882	.02872	-3.22	0.001
poor*|	.0242252	.02739	0.88	0.376
villmid*|	-.0713809	.02702	-2.64	0.008
villsec*|	.0474567	.06867	0.69	0.490
netloan |	1.76e-06	.00000	2.76	0.006
landowner*|	-.0912404	.05913	-1.54	0.123
agtech2 |	-.0000214	.00001	-2.73	0.006
agtech4 |	-7.35e-07	.00000	-0.80	0.426

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Table 3.3: Marginal probabilities corresponding to equation 3.3

variable |	dy/dx	Std. Err.	z	P>|z|
male*|	-.2822471	.02699	-10.46	0.000
oldest*|	.0969143	.04136	2.34	0.019
headedu |	-.0224476	.0062	-3.62	0.000
momedu |	-.0433686	.01272	-3.41	0.001
hhsize |	-.0103304	.00312	-3.31	0.001
Hinduhh*|	-.0536651	.05	-1.07	0.283
hhcaste*|	-.0919181	.02857	-3.22	0.001
poor*|	.0477125	.02925	1.63	0.103
villmid*|	-.0696684	.02662	-2.62	0.009
villsec*|	.040567	.06727	0.60	0.546
netloan |	1.65e-06	.00000	2.56	0.010
agtech11 |	.0000488	.00046	0.11	0.916
agtech22 |	-.0000195	.00001	-2.58	0.010
agtech33 |	-.0004191	.00019	-2.21	0.027

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Table 3.4: Marginal probabilities corresponding to equation 3.4

variable |	dy/dx	Std. Err.	z	P>|z|
male*|	-.2798976	.02687	-10.42	0.000
oldest*|	.0854634	.03933	2.17	0.030
headedu |	-.0218167	.00619	-3.52	0.000
momedu |	-.0418377	.01287	-3.25	0.001
hhsize |	-.0093867	.00311	-3.02	0.003
Hinduhh*|	-.0507652	.04817	-1.05	0.292
hhcaste*|	-.092588	.02868	-3.23	0.001
poor*|	.0301548	.02761	1.09	0.275
villmid*|	-.0652862	.02694	-2.42	0.015
villsec*|	.0419454	.06765	0.62	0.535
netloan |	1.79e-06	.00000	2.81	0.005
agtech22 |	-.0000221	.00001	-2.74	0.006
agtech44 |	-8.02e-07	.00000	-0.84	0.401

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Table 4.1: Results related to children who belong to families below the poverty line

Variable	(4.1.1)[1,2]	(4.1.2)[1,2]	(4.1.3)[1,2]	(4.1.4)[1,2]
Male	-1.9 (-6.23)***	-1.84 (-6.16)***	-1.82 (-6.17)***	-1.73 (-6.03***
Oldest	0.62 (1.51)	0.58 (1.49)	0.58 (1.42)	0.55 (1.46)**
Headedu	-0.09 (-1.37)	-0.09 (-1.35)	-0.11 (-1.6)	-0.1 (-1.6)
Momedu	-0.08 (-0.61)	-0.05 (-0.35)	-0.11 (-0.72)	-0.068 (-0.13)
Hhsize	-0.05 (-1.17)	-0.04 (-0.79)	-0.06 (-1.4)	-0.04 (-0.93)
Hinduhh	-0.51 (-0.86)	-0.55 (-0.94)	-0.51 (-0.84)	-0.54 (-0.91)
Hhcaste	-1.55 (-2.42)**	-1.61 (-2.53)**	-1.54 (-2.45)**	-1.6 (-2.58)**
Villmid	-1.2 (-2.8)**	-1.13 (-2.64)**	-1.13 (-2.81)**	-1.03 (-2.58)**
Villsec	1.52 (2.02)**	1.59 (2.14)**	1.56 (2.11)**	1.63 (2.19)**
Landowner	-0.82 (-1.92)*	-0.85 (-1.99)*		
Agtech1	0.0008 (0.23)			
Agtech2	-0.0002 (-0.52)	-2.86e-06 (-0.06)		
Agtech3	-0.002 (-1.54)			
Agtech4		3.15e-07 (-0.07)		
Agtech11			-0.001 (-0.41)	
Agtech22			-0.0002 (-0.55)	-0.0001 (-0.23)
Agtech33			-0.003 (-1.61)*	
Agtech44				-3.65e-07 (-0.07)
Pseudo R^2	0.19	0.18	0.18	0.17
N	297	297	297	297

1. The number in parentheses represents the z value with * representing significance at 10%, ** 5%, *** 1%.
2. Coefficient values using marginal probabilities for the results are available upon request

Table 4.2: Results related to children who belong to families above the poverty line

Variable	(4.2.1)[1,2]	(4.2.2)[1,2]	(4.2.3)[1,2]	(4.2.4)[1,2]
Male	-1.79 (-8.85)***	-1.8 (-8.9)***	-1.78 (-8.85)***	-1.79 (-8.9)***
Oldest	0.62 (2.39)**	0.55 (2.16)**	0.61 (2.36)**	0.54 (2.13)**
Headedu	-0.16 (-3.08)***	-0.16 (-3.04)***	-0.16 (-3.09)***	-0.15 (-3.04)***
Momedu	-0.38 (-3.58)***	-0.38 (-3.62)***	-0.38 (-3.59)***	-0.38 (-3.65)***
Hhsize	-0.05 (-2.38)***	-0.05 (-2.28)***	-0.05 (-2.42)***	-0.05 (-2.33)***
Hinduhh	-0.36 (-1.12)	-0.3 (-0.95)	-0.35 (-1.09)	-0.3 (-0.95)
Hhcaste	-0.49 (-1.81)*	-0.48 (-1.79)*	-0.49 (-1.83)*	-0.48 (-1.8)***
Villmid	-0.33 (-1.41)	-0.33 (-1.4)	-0.32 (-1.37)	-0.31 (-1.31)
Villsec	-0.31 (-0.59)	-0.31 (-0.6)	-0.32 (-0.62)	-0.34 (-0.66)
Landowner	-0.25 (-0.6)	-0.28 (-1.65)*		
Agtech1	-0.0002 (0.27)			
Agtech2	-0.0002 (-3.91)***	-0.0002 (-4.03)***		
Agtech3	-0.003 (-1.67)*			
Agtech4		-0.00004 (-0.8)		
Agtech11			-0.002 (-0.38)	
Agtech22			-0.0002 (-3.91)***	-0.0002 (-4.01)***
Agtech33			-0.003 (-1.65)*	
Agtech44				-0.00004 (-0.81)
Pseudo R^2	0.22	0.22	0.22	0.22
N	812	812	812	812

1. The number in parentheses represents the z value with * representing significance at 10%, ** 5%, *** 1%.
2. Coefficient values using marginal probabilities for the results are available upon request

Table 5.1: Results related to children who belong to families with less than 1 of land

Variable	(5.1.1)[1,2]	(5.1.2)[1,2]	(5.1.3)[1,2]	(5.1.4)[1,2]
Male	-1.9 (-7.63)***	-1.92 (-7.63)***	-1.88 (-7.48)***	-1.85 (-7.42***
Oldest	0.91 (3.0)***	0.86 (2.91)**	0.85 (2.85)**	0.78 (2.71)**
Headedu	-0.1 (-1.47)	-0.09 (-1.4)	-0.11 (-1.56)	-0.1 (-1.49)
Momedu	-0.49 (-2.75)**	-0.47 (-2.63)**	-0.52 (-2.88)**	-0.49 (-2.74)**
Hhsize	-0.1 (-2.39)**	-0.09 (-2.21)**	-0.1 (-2.58)**	-0.09 (-2.36)
Hinduhh	-0.62 (-1.38)	-0.63 (-1.44)	-0.58 (-1.32)	-0.6 (-1.38)
Hhcaste	-1.2 (-2.32)**	-1.29 (-2.46)**	-1.11 (-2.26)**	-1.2 (-2.44)**
Villmid	-0.54 (-1.7)*	-0.48 (-2.64)**	-0.48 (-1.6)	-0.38 (-1.26)
Villsec	1.02 (1.8)*	1.01 (1.78)*	0.95 (1.7)*	0.95 (1.7)*
Landowner	-0.74 (-2.18)**	-0.83 (-2.43)*		
Agtech1	-0.002 (-0.58)			
Agtech2	-0.0004 (-0.8)	-0.00006 (-0.86)		
Agtech3	-0.001 (-1.46)			
Agtech4		2.14e-06 (-0.36)		
Agtech11			-0.002 (-0.58)	
Agtech22			-0.0004 (-0.8)	-0.0001 (-0.89)
Agtech33			-0.002 (-1.8)*	
Agtech44				-3.07e-06 (-0.49)
Pseudo R^2	0.21	0.2	0.21	0.19
N	445	445	445	445

1. The number in parentheses represents the z value with * representing significance at 10%, ** 5%, *** 1%.
2. Coefficient values using marginal probabilities for the results are available upon request

Table 5.2: Results related to children who belong to families with more than 1 of land

Variable	(5.2.1)[1,2]	(5.2.2)[1,2]
Male	-1.87 (-8.44)***	-1.8 (-8.22)***
Oldest	0.31 (0.92)	0.24 (0.74)
Headedu	-0.16 (-2.9)**	-0.16 (-3.11)***
Momedu	-0.25 (-2.65)***	-0.23 (-2.54)**
Hhsize	-0.05 (-2.4)**	-0.05 (-2.1)**
Hinduhh	-0.35 (-0.82)	-0.23 (-0.57)
Hhcaste	-0.74 (-2.58)**	-0.69 (-2.37)**
Villmid	-0.53 (-1.78)*	-0.57 (-1.88)*
Villsec	-0.31 (-0.53)	-0.32 (-0.53)
Agtech1	0.01 (2.24)**	
Agtech2	-0.0002 (-4.68)***	-0.0002 (-4.55)***
Agtech3	-0.02 (-2.29)**	
Agtech4		0.0001 (0.68)
Pseudo R^2	0.22	0.21
N	664	664

1. The number in parentheses represents the z value with * representing significance at 10%, ** 5%, *** 1%.
2. Coefficient values using marginal probabilities for the results are available upon request

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