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# CHILD LABOR AND SCHOOL ENROLLMENT IN RURAL INDIA: WHOSE EDUCATION MATTERS?

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This paper empirically analyzes the determinants of child labor and school enrollment in rural Andhra Pradesh, India. A village fixed-effect logit model for each child is estimated with the incidence of child labor or school enrollment as the dependent variable, in order to investigate individual and household characteristics associated with the incidence. Among the determinants, this paper focuses on whose education matters most in deciding the status of each child, an issue not previously investigated in the context of the joint family system. The regression results show that the education of the child's mother is more important in reducing child labor and in increasing school enrollment than that of the child's father, the household head, or the spouse of the head. The effect of the child's mother is similar on boys and girls while that of the child's father is more favorable on boys.

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## I. INTRODUCTION

A high incidence of child labor and a very low school enrollment of children continue to pose serious problems for India. According to the International Labour Organization International Programme on the Elimination of Child Labour (ILO-IPEC 2005), throughout the Asia and Pacific region about 127 million children in the 5–14 years age group are engaged in work. Of this total, more than 100 million can be attributed to India alone.[1] There have been a number of attempts to eradicate child labor and to send children to school in India. These include the imposition of legal action against child labor, as well as trade sanctions, the education of parents, and the provision of education subsidies. Nevertheless, judging from the current estimates of the number of working children, the impact of these policies has been limited. Our understanding of the determinants of child labor is also limited, though the quantity of theoretical and empirical work on child labor has increased rapidly in recent years (Basu 1999; Basu and Tzannatos 2003).

On child labor in India, there exist a few microeconomic studies that empirically analyze the determinants of child labor. These include Aggarwal (2004), Basu, Das, and Dutta (2003), Deb and Rosati (2002), Edmonds, Pavcnik, and Topalova (2005), and Sakamoto (2006). These studies have one feature in common: they employ datasets collected by way of the large-scale sample household surveys conducted by national and international agencies. In other words, the authors of these papers were seldom involved in the design and implementation of the surveys on which they have based their research. This shortcoming limits the data for the analysis to information derived solely from standardized household questionnaires. There may be some empirical studies, especially in sociology or anthropology, which analyze child labor and school enrollment based on detailed village surveys.

But the findings from such studies cannot directly contribute to our understanding of the microeconomic mechanisms of child status. Since child labor and school enrollment result from decision making within households, we believe that it is critically important to analyze the incidence of such phenomena as issues of intrahousehold resource allocation within a household (Fuwa *et al*. 2006a).

With this belief in mind, we conducted a special household survey in rural Andhra Pradesh to collect detailed information on intrahousehold resource allocation (Fuwa *et al*. 2006a). The rich information thus collected and the authors' close involvement in the survey distinguishes the analysis of this paper from those by the above-mentioned authors. Methodologically, we follow the approach typically adopted in the existing studies on child labor, using cross-section data: a village fixed-effect logit model for each child with the incidence of child labor or school enrollment as the dependent variable. By estimating the logit model, we can identify individual and household characteristics that are associated with the incidence. A unique feature of this study is its focus on a previously unexplored question, namely whose education matters most in deciding between child labor and school enrollment? Most of the above-mentioned studies can be classified into either those analyzing children belonging to a standard nuclear family where the education variables of concern are defined as those of the child's father and mother, or, those using the education of the household head. This paper extends the analysis to children belonging to other types of household and investigates whether the education levels of the household head and his/her spouse are better indicators than those of the child's parents. As far as we know, this is the first attempt to investigate the question of whose education matters in the context of child labor.[2] The broadening of the analysis is also important in practical terms because of the prevalence in India of various types of joint family, including three-generation families with more than one couple of the second generation living together.[3]

The paper is organized as follows. Section II describes the dataset, characterizing children's activities observed in our dataset. Section III presents empirical models in which we attempt to relate reduced-form regression models with theoretical models of intrahousehold resource allocation. Section IV presents regression results using a logit model for the incidence of child labor and school enrollment. Section V concludes the paper.

## II. DATA

In the quantitative analysis used in this paper, we employ micro household data collected in Andhra Pradesh, India, in February/March 2005. Approximately 400 households were surveyed from 32 villages in two *mandal*s (administrative blocks) in Kurnool District, Andhra Pradesh. The study villages and the sample households were chosen randomly through variable probability sampling (see Fuwa *et al*. [2006a] for the sampling ratios). The study villages are remote from cities and depend on both irrigated and unirrigated agriculture.[4] In the appendix of his paper, Ito (ed.) (2005) describes the questionnaires that were used by local collaborators/investigators for this survey.

In order to analyze child labor empirically, we need to clearly define both "child" and "work." This apparently simple task is in reality quite difficult. First, the concept of "child" differs greatly across societies and cultural settings. In western societies, it is customary to define "child" by the chronological age of a person, but in many societies, cultural and social factors are taken into account as well. Second, the concept of "work" cannot be defined easily. There are many different activities in which children can be engaged. Children can help with domestic work and work on the farm or in the household enterprise, or they can participate in the labor market. It is not a straightforward task to draw a clear line between "work" and "non-work" child activities. A key question is whether the arrangement is "exploitative." At an extreme level, child labor can take the form of bonded labor or quasi-slavery. A debt incurred by the parents can be the "bond" whereby a child is forced to work (Grootaert and Kanbur 1995).

Taking into account these difficulties, the incidence of child labor and children's enrollment in school is defined in this paper as a child's usual economic activity. Borrowing the classification in the ILO standards, we cover children in the 5–14 years age group. Not only wage labor but also unpaid labor inside the household, on household enterprises (such as crop farming, livestock husbandry, and non-farm business), are included as "work" since the fruit of child labor is (potentially) marketed. This type of work is called "market work." It may be more difficult to reach a consensus on whether or not we should include household chores such as cleaning, water fetching, baby care, and so on. In this paper, we call such work "domestic work" and employ both a narrower definition of child labor (labeled $cl_1$) that includes only market work, and a wider definition of child labor (labeled $cl_2$) that includes both market and domestic work. Since the most important activity that competes with working for a child's time endowment is schooling, another variable labeled *enrl* is calculated. This is a dummy variable that takes one for a child who is enrolled in school.

In Table 1, the incidence of child labor and school enrollment in our dataset is shown together with similar estimates based on larger household surveys. In large-scale sample household surveys in India, such as the NSS (National Sample Survey) and LSMS (Living Standard Measurement Study) datasets, full information on detailed activities may not be available for younger children. For instance, in the LSMS survey conducted in Bihar and Uttar Pradesh (henceforth "the UP-Bihar LSMS"), a different list is used to ask younger children, aged nine years or less, about their usual status. Therefore, Table 1 reports the incidence ratio for children aged 10–14 years (the middle school age). At the all-India level (the NSS dataset), the incidence decreased between 1993/94 and 1999/2000 regardless of the choice of $cl_1$ and $cl_2$. The incidence ratio was below 10% in the more recent period under the narrower definition of child labor. The decline was observable in both rural and urban areas. By contrast, the school enrollment ratio increased during the same period from 71% to 76%. In UP and Bihar, where income poverty is more severe than in other regions of India, the child labor incidence ratio was reported to be around 11% (the narrower definition) and 28% (the wider definition). The UP-Bihar LSMS data show a huge difference between boys and girls. The incidence of domestic work is so high among girls that their school enrollment ratio is only 54% as against 80% for boys.

Our dataset shows a gender disparity similar to that found in the UP-Bihar LSMS data. The incidence of domestic work is much higher for girls than for boys; the school enrollment ratio is much lower for girls than for boys. There are two differences between our results and those from the UP-Bihar LSMS. First, the incidence of market work is higher for girls than for boys in AP while it is lower for girls in UP and Bihar. This could be due to the more careful way in which we examined children's activities in the field. We suspect that in NSS or LSMS, those children working mostly inside the house are labeled as doing domestic chores regardless of the actual nature of their activities. Our field observations suggest that most of the work done by these children is related to market activities such as the processing of farm products and the supervision of livestock animals. Another possibility is that the difference reflects the greater conservatism of people in Bihar and UP with regard to female employment. Given the income levels, female wage work is less prevalent in Bihar and UP than in the South (Aggarwal 2004). A second difference concerns the level of child labor, which is much higher in our dataset than in the UP-Bihar and NSS datasets. This reflects our sampling design, and the fact that we intentionally surveyed regions with a higher concentration of child labor (see Fuwa *et al*. 2006a).

Table 2 reports more details of children's activities as well as information on younger children aged 5–9 years (the primary school age). Among children aged 10–14 years, agricultural wage labor is the dominant type of employment, followed by employment relating to the family's own farming and livestock work. For younger children, the child labor incidence is lower than for elder children but still as high as 9.6% ($cl_1$) and 12.6% ($cl_2$). Among younger children, livestock work is the most important form of employment, followed by domestic work and agricultural wage labor. Thus, ignoring child labor among younger children introduces a serious bias into any study on child labor and intrahousehold resource allocation in India. It is of interest that the school enrollment ratio in Table 2 is slightly higher than the ratio of children whose usual status is reported as "student." The difference is explained by the presence of children who both work and study but who give working as their main activity. Fortunately, our dataset allows much detailed analysis of the coexistence of work and study, because we have collected detailed information on the time use of each child.

To summarize, our dataset allows more detailed analysis of child labor than types of analysis based on the existing datasets. First, since we include younger children, our coverage is wider. Second, we provide more detailed information, including information on individual time use. For these reasons, the analysis of child labor using the cross-section variation in this paper can contribute to a deepening of our understanding of child labor in developing countries in general and in less-developed regions in India in particular.

## III. EMPIRICAL MODELS

### A. *Empirical Strategy*

We assume that the status of each child *i* is decided either by the household as a unit or by the parents and grandparents of the child through a collective bargaining process (see Fuwa *et al*. 2006a, for a short survey and for examples of these household models). We acknowledge that the education of a child is both an investment for the future and a form of current consumption (a superior good) for the parents. Thus, under the unitary framework, the determinants of the child's status include market returns of child labor and schooling, the interest rate and credit constraints in which the household must operate, and the preferences of the household. When a household is poor, its children are more likely to work and less likely to be in school, because credit constraints are more likely to be binding, time preferences are in favor of current consumption, and consumption preferences for education may be low. Under the collective framework, additional variables called "extra-household environmental parameters" (EEPs) should also affect consumption. These include variables such as local sex ratios, divorce law legislation, and the degree of prohibition on market work by gender, through changing the distribution rule within the household and the wife's bargaining power against her husband.

To infer such a process of intrahousehold resource allocation, this paper estimates reduced-form regression models. The dependent variable is $cl_{1i}$ (the dummy variable for the market work for child *i*) or $cl_{2i}$ (the dummy variable for the wider definition of child labor for child *i*) or $enrl_i$ (school enrollment dummy for child *i*). Since child labor and schooling are usually regarded as substitutes, we expect the patterns of coefficients in the $enrl_i$ regression to be the opposite to those in the $cl_{1i}$ and $cl_{2i}$ regressions. But how exact is the contrast? By examining the contrast, we can infer the substitutability of labor and schooling for a child.[5] Since the dependent variable is binary and we introduce village fixed effects, we employ a logit specification.

We restrict the list of explanatory variables to those that are exogenous to decision-making with respect to the child status. In other words, we do not attempt to include variables such as the household's credit constraint, household income, or the parents' working status, because these variables are endogenously decided, simultaneously with the working/schooling status of each child (for an attempt to incorporate these variables and estimate models using instrumental variables, see Sawada *et al*. [2006]). Because of this very reduced-form approach and the nature of our dataset (single cross-section), it may be difficult to interpret the results as the true "determinants" of child labor. Our intention is to show which characteristics of individual children and households are associated with the incidence of child labor and then to compare the results with major hypotheses of the determinants of child labor in the existing literature. Since a formal test of causality is not attempted, the regression analysis in this paper is descriptive in nature.

### B. *Empirical Models for Children in the Standard Type Households*

We first estimate models using the subset of children aged 5–14 years where the father is the household head and where the mother is the spouse of the household head. The household head status was assigned to one of the household members based on the response we obtained from the household. The member who was assigned as the head is a person who is present in the household and is responsible for decision-making. Most of these children belong to a nuclear family with both of their parents alive. We call such a family "the standard family type." Among the 1009 children reported in Table 2, about 75% belong to the standard family type.

The following independent variables are included in the basic model for the children belonging to the standard family type (Model 1-1):

1. Individual characteristics of a child: *age*, *age_squared* (defined as $(age\text{-}5)^2$, to capture non-linearity of the age effect), and *sex* (a dummy for a girl).
2. Household characteristics: *lit_fat* (the literacy dummy for the father of the child), *lit_mot* (the literacy dummy for the mother of the child), *lit_fat∗sex* and *lit_mot∗sex* (the cross terms between the parents' education and the girl dummy), *hhsize* (the number of household members), *bplhold* (a dummy variable for the ration card holder under the Public Distribution System of the Government of India), *asset* (the total amount of household assets in 100,000 Rs.), and dummy variables for the community (religion and wider caste groupings) of the household.

The cross terms *lit_fat∗sex* and *lit_mot∗sex* are included to investigate one aspect of the question "whose education matters?" If the mother's education is more important to girls and the father's education is more important to boys in reducing child labor and in increasing school enrollment, we expect *lit_fat∗sex* and *lit_mot∗sex* to have the opposite signs (Thomas 1994; Quisumbing and Maluccio 2003). Variable *bplhold* is a proxy for the government's designation that the household is not rich. Thus the variable is expected to capture the effect of poverty or the effect of households' interaction with poverty reduction policies. The variable *asset* is meant to capture the wealth effect, which is theoretically predicted to have a negative impact on child labor and a positive impact on school enrollment.

The community dummies are: *SC* (scheduled castes), *ST* (scheduled tribes), *UMH* (upper and medium Hindu castes), and *Muslim* (Muslims). The reference is those households belonging to so-called other backward classes (*OBC*). In India, it is often claimed that scheduled castes and tribes are backward strata with lower interests in education. If this is correct, we expect coefficients on *SC* and *ST* to be positive on $cl_1$ ($cl_2$) and negative on *enrl*. We will examine whether this holds true even when we control for other individual and household characteristics. We also expect that the inclusion of community dummies (or more detailed caste fixed effects) reduces the possible bias due to omitted variables at the household level.

3. Village fixed effects: these collectively control for differences in market conditions and school qualities. We do not attempt to interpret coefficients on the village fixed effects in this paper.

In Model 1-2, *asset* is disaggregated into four sources: *landval* (the value of owned land), *asset_ag* (the value of farming equipment such as tubewells, tractors, and bullock carts), *asset_lv* (the value of livestock), and *asset_hh* (the value of house and household equipment such as bicycles and televisions). The motivation of this extension is to examine the hypothesis that the wealth effect to reduce child labor (to increase school enrollment) is attenuated by the productivity effect through family labor when the wealth takes the form of land or livestock. If livestock require careful looking after by family labor, a larger number of animals implies that the marginal return to child labor on livestock increases, thus leading to an increase of child labor, and canceling out the child-labor-reducing effect of livestock as a source of wealth (Drèze and Kingdon 2001). The land asset can also have a similar characteristic (Bhalotra and Heady 2003). We can test whether each source of assets has a different impact by a $\chi^2$ test for the null hypothesis that all coefficients on *landval*, *asset_ag*, *asset_lv*, and *asset_hh* are the same. As a robustness check, we also estimate models with *landval* replaced by the acreages of irrigated and unirrigated plots.

In Model 1-3, hhsize is disaggregated demographically into the following groups: infants (the number of household members in the 0–4 years age group, *children* (the number of household members in the 5–14 years age group), and *adeld* (the number of household members aged 15 years or older). This should allow us to examine the hypothesis that a sibling effect exists: when the child has siblings that compete for resources required for schooling, we expect *children* to have a negative effect on enrl; when the child has younger siblings that require looking after, we expect *infants* to have a positive effect on $cl_2$ (but not on $cl_1$) (Basu, Das, and Dutta 2003; Rosati and Rossi 2003). The positive effect of *infants* on $cl_2$ may be larger on girls than on boys, which we can test by the significance of the coefficient on the cross term *infants*sex*. By contrast, if elderly people can help the child going to school, we expect *adeld* to have a positive effect on enrl and a negative effect on child labor. We can test whether each demographic component has a different impact by a $\chi^2$ test for the null hypothesis that all coefficients on *infants*, *children*, and *adeld* are the same.

Model 1-4 includes additional variables that characterize the grandparents of the child. In many cases, grandparents are dead already or live separately from the current household (note that we limit the analysis to children who belong to the standard household type). Therefore, a prediction of unitary household models is that their characteristics should not affect the child's working status if we sufficiently control for the returns of his/her labor and schooling and the household's wealth and credit access status. If these characteristics affect the child's working status, it may be a reflection of the father's and mother's bargaining parameters, which should affect the child's working status under the assumptions of non-unitary household models. In other words, we use the characteristics of grandparents of the child as EEPs to distinguish unitary and non-unitary household models.

This test may not be ideal, since our dataset is only a cross-section so that omitted-variable bias may be serious enough. We also acknowledge that the significance of coefficients on any grandparental variables does not rule out preference-based explanations consistent with unitary models if certain traits or preferences may be transmitted through generations. For example, a mother whose mother is educated may reveal a preference for greater investments on her daughter and such preference is reflected in the household's unitary utility function. Thus, we need to be careful in the interpretation of the results.

In concrete terms, the additional variables include: *hdf_lit* (literacy of the father of the child's father), *spf_lit* (literacy of the father of the child's mother), *f_land* (land holding of the father of the child's father, with an acre of dry land weighted as a half acre of irrigated land), *m_land* (land holding of the father of the child's mother), *hdp_adiff* (the age difference of the parents of the child's father), and *spp_adiff* (the age difference of the parents of the child's mother). Though we have information on the literacy of grandmothers of the child, these variables are not included since the majority of observations are zero. We can test whether these proxies for EEPs affect child labor and schooling by a $\chi^2$ test for the null hypothesis that all coefficients on these variables are zero.

#### C. *Empirical Models for All Children*

In models using data relating to all children, two issues are investigated. The first is the effect of household type on child labor. In Model 2-1, variables similar to those in Model 1-1 are employed. When we broaden the sample, we encounter several observations where *not both* of the parents of a child are included in the household (e.g., either one or the other of the parents is dead or permanently absent). To exploit the full information derived from our sample, we did not exclude these observations but assigned zero (i.e., the median value) of *lit_fat* and *lit_mot* when either of the parent's variables is missing and then created a dummy variable for incomplete information on the parent (*no_fat* and *no_mot*). In addition, we have compiled household-level dummies for female-headed households (*hd_sex*) and non-standard type households (*nonnucl*). These four dummy variables are added to the model.

The second issue to be analyzed using the expanded dataset is the question "whose education matters?" recognizing the reality that various family types co-exist in India. For those children belonging to a three-generation family with the grandfather of the child serving as the household head, what matters for the child's status may not be a decision by his or her own parents, but a decision by the household head (i.e., his or her grandparents).[6] If this is true, the correct measures of parental education may not be *lit_fat*, *lit_mot*, and their cross terms with sex, but *hd_lit* (the literacy dummy for the household head), *sp_lit* (the literacy dummy for the spouse of the household head), and their cross terms with sex. Therefore, in Model 2-2, *lit_fat* is replaced by *hd_lit* and *lit_mot* is replaced by *sp_lit*, and results from Model 2-1 and Model 2-2 will be compared. For those children belonging to the standard household type, the two sets of variables are exactly the same. For those children belonging to the non-standard household type, they are different. In the literature on the productivity of household enterprises in developing countries, the question "whose education matters most?" has been investigated intensively (Yang 1997a; 1997b; Jolliffe 2002; Laszlo 2005). These studies found that the education level of the household head may not be the best indicator. By contrast, investigations of this kind have not been attempted in the child labor context. As far as we know, this paper is the first attempt in this direction.

In Model 2-3, we adopt specifications using both parents' and heads' education. Potentially, we have eight variables to include: *lit_fat*, *hd_lit*, *lit_mot*, *sp_lit*, and their cross terms with *sex*. Because of multicollinearity, we cannot include all of them. Therefore, we include only those cross terms that were statistically significant either in Model 2-1 or in Model 2-2. Through $\chi^2$ tests, we can identify which of these variables can be eliminated. Our approach of choosing the best education indicators by comparing Models 2-1 and 2-2 and then conducting exclusion tests on Model 2-3 is similar to the one adopted by Jolliffe (2002) in his investigation on the productivity of household enterprises.

## IV. ESTIMATION RESULTS

Table 3 reports summary statistics of the empirical variables. Estimation results based on a village fixed-effect logit specification are reported in Tables 4–5. The coefficients on village fixed effects are not reported in the interests of brevity. The coefficients on the community dummies (*SC*, *ST*, *UMH*, and *Muslim*) are reported with *OBC* as the reference.

#### A. *Children Belonging to the Standard Family Type*

First, the basic results (Model 1-1 in Table 4) show that a child who is older and female is more likely to work and less likely to be enrolled in school. These effects are statistically significant and the coefficient on the female dummy is very large. The coefficient on the gender dummy is larger on $cl_2$ than on $cl_1$. This is because girls are more likely to work domestically. These patterns are very robust: all of Models 1-1 to 2-3 show similar results.

Second, more educated parents send their children less to work and more to school. This is a confirmation of the established regularity throughout the developing world. The existing empirical studies on India have found a similar result (Aggarwal 2004; Basu, Das, and Dutta 2003; Deb and Rosati 2002; Drèze and Kingdon 2001; Sakamoto 2006). This is consistent with both the wealth effect hypothesis (educated parents are usually richer than uneducated parents) and the preference effect hypothesis (educated parents value education more). Note that both hypotheses are consistent with unitary and non-unitary household models.

Third, what is more interesting is that the effect of education is much stronger for the mother's education than for the father's. This may seem readily consistent with the bargaining hypotheses under non-unitary household models: mothers prefer more education for children than fathers, and the mothers' bargaining power is increased by the mothers' relative position in education. However, since education also affects market and reservation wages of mothers and fathers, our results can also be compatible with the unitary approach (Doss 1996). For instance, better educated mothers may raise the returns to children's education more than better educated fathers, since, for example, (stay-home) mothers are arguably in a better position to facilitate children's learning (for example, through helping with their homework) than are fathers. In any case, all specifications of Models 1-1 to 2-3 show that mothers' education matters more than fathers'. The difference between fathers' and mothers' education has been observed in South Asia, in studies by Drèze and Kingdon (2001), Rosati and Rossi (2003), and Sakamoto (2006). However, the gender contrast found in these studies is less pronounced than the one found here.

Fourth, the cross terms between parents' education and girls' dummy show a contrast between the father's and the mother's education. The effect of the father's education is favorable on boys (negative on child labor and positive on enrollment), but the favorable effect is mostly cancelled out on girls. The canceling impact shown by the cross term is statistically significant on $cl_2$. Therefore, our data show that the father's favorable influence mostly goes towards boys, and not towards girls. In contrast, the coefficient on the cross term between mothers' education and girls' dummy is very small. Its sign changes depending on the specification, but in none of them is the coefficient statistically significant. Therefore, the regression results show that the mother's favorable influence is directed equally towards boys and girls. This finding is similar to the one reported by Quisumbing and Maluccio (2003), though our results are more clear-cut than theirs.

Fifth, the household demographic size (*hhsize*) has an imprecisely estimated coefficient, contrasting with the finding by Ray (2000) that household size has a positive effect on the incidence of child labor in India. All coefficients are statistically insignificant when children belonging to the standard household type are analyzed (Models 1-1 to 1-4). If we can regard elder siblings' working status as exogenous to younger siblings, because they are predetermined and parents are not likely to take into account future births when deciding on elder siblings' schooling, then adding elder siblings' working status can separate out these countervailing forces. If the child is the eldest and *hhsize* is large, then this child will be more likely to work, whereas if this child is the youngest and the elder siblings are working, then this child may be more likely to go to school. To test for this prediction, we disaggregate *hhsize* in Model 1-3 into *infants* (the number of household members aged four years or less), *children* (the number of household members aged 5–14 years), and *adeld* (others). The results show that the null hypothesis that these three have the same coefficient is not rejected in all three regressions. Addition of the cross term between *infants* and *sex* did not change these results and the coefficient on the cross term is statistically insignificant.

Sixth, *bplhold* has an insignificant coefficient on child labor while it has a positive and significant coefficient on school enrollment. If this variable captures the poverty effect, the results seem strange (poorer households that deserve ration cards send their children to school more). This variable may capture the effect of households' interaction with local administrations: households with ration cards may have superior access to the local administration so that they send their children to school more.

Seventh, the coefficient on *asset* is negative on child labor and positive on school enrollment, as consistent with the poverty effect hypothesis. However, all of these coefficients are statistically insignificant. In other words, child labor is found to be almost constant over the (sampled) support of wealth distribution, holding other variables fixed. This indicates that low wealth level, conditional on other covariates, is not a sufficient condition of child labor.

If we disaggregate the wealth into four sources (Model 1-2), the results do not change much: the coefficients on wealth variables are statistically insignificant. Interestingly, the positive impact of *landval* on school enrollment is marginally significant (*p*-value = 0.12), implying that landed households are more likely to send their children to school. To check the robustness of the results,[7] other specifications regarding the land asset variable were estimated. The specifications using the acreage of both rain-fed and irrigated plots and the IV estimation using the acreage of both rain-fed and irrigated plots as identifying IVs for *landval* yielded similar results: the land variables are not significant in explaining child labor while their positive impact on school enrollment is marginally significant. Thus, the finding of this paper is robust. We interpret this finding as suggesting that the productivity effect through family labor when wealth takes the form of land may not be large in our case, indicating that land ownership does not affect child work very much. This is contrary to the finding by Bhalotra and Heady (2003) that in Pakistan, land ownership leads to more working by children, but is consistent with the finding by Deb and Rosati (2002) that in India, children of landless households are more likely to work. One possibility is that our survey was conducted in a drought year, resulting in a smaller productivity effect through family labor when wealth takes the form of land. The effect of livestock in our sample is insignificant in contrast to the finding by Drèze and Kingdon (2001) that livestock wealth decreases school enrollment in India. The difference in the findings might be attributable to the smaller importance of dairy livestock farming in the study region than in North India.

Eighth, the results for Model 1-4 show that some of the characteristics of grandparents of the child (proxy for EEPs) are statistically significant.[8] For instance, *spf_lit* (literacy of the father of the child's mother) decreases child labor $cl_2$ and increases school enrollment. The $\chi^2$ statistics to test the null hypothesis that all coefficients on these EEPs are zero show that the null hypothesis is rejected for the enrollment regression. Therefore, we obtain evidence, though weak, that these proxies for EEPs do affect child status, the evidence being of a kind that rejects the unitary household approach. This argument is valid if these variables represent EEPs only. For instance, the results show that the literacy of the father of the child's mother increases school enrollment even after controlling for the parents' education. Although it is tempting to interpret this as evidence against unitary models, this can be interpreted under the unitary framework as well: these variables may capture the household's access to quality education that is not sufficiently controlled by other variables. If this is the case, the variables included in Model 1-4 may not good proxies for EEPs.

Finally, the effects of the community dummies remain even after controlling for individual and household characteristics and village fixed effects. In the child labor regressions, coefficients on *SC*, *UMH*, and *Muslim* are negative with statistical significance, implying that households belonging to scheduled castes, upper and medium castes, and Muslims are less likely to send children to work than households belonging to "other backward classes." In the enrollment regression, coefficients on *UMH* and *Muslim* are positive and statistically significant, implying that households belonging to upper and medium castes and Muslims are more likely to send children to school than households belonging to "other backward classes." These effects for the upper and medium castes are as expected since in the rural setting of India, these castes are regarded as socially advanced. However, the signs of the coefficients on *SC* and *Muslim* dummies are opposite to our expectation and to the findings of Deb and Rosati (2002), Drèze and Kingdon (2001), Aggarwal (2004), and Sakamoto (2006).[9] Though not significant in several cases, the signs of the coefficients on *ST* also suggest that the welfare of scheduled-tribe children is better than that of children of "other backward classes." These households are more enthusiastic about schooling and more averse to child labor than "other backward classes." This may reflect the impact of civil movements in rural Andhra Pradesh to improve the social conditions of the scheduled castes, scheduled tribes, and Muslim households.

### B. *Results Based on the Sample of All Children*

To investigate the effects of family types and other household members' education, models in the previous subsection were extended to cover all children, including those belonging to households that are not of the standard type (i.e., households in which the father of the child is the household head and the mother of the child is the head's spouse). The results are reported in Table 5.

First, the results of Model 2-1 show that those variables included in Model 1-1 have coefficients with the same sign and similar significance. Older children are more likely to work, girls are more likely to work and less likely to go to school, the education level of the parents reduces child labor and increases schooling, with a bigger impact from the mother's education, and the status of ration card holders increases schooling. Thus the findings shown in the previous subsection are robust.

Second, households headed by females are more likely to send their children to work and are less likely to send them to school. This is a confirmation of previous studies in India (see for example Aggarwal 2004). However, the effect on child labor is small and statistically insignificant, while that on schooling is significant. Therefore, asymmetric effects are found, suggesting that child labor and schooling are not perfect substitutes (Bacolod and Ranjan 2003; Basu, Das, and Dutta 2003; Deb and Rosati 2002).

Third, households belonging to the non-standard family type are less likely to send their children to work and are more likely to send them to school. The coefficients on *nonnucl* are negative on child labor and positive on schooling with statistical significance, a finding that is similar to the result reported by Aggrawal (2004). Given the same household size and household assets, children belonging to the non-standard family type are better off. This can be attributed to the greater division of labor within a joint family, a situation that improves children's comparative advantage in learning. How this is achieved exactly is an issue left for further research that will focus on more detailed information on the demographic structure.

Fourth, the regression results show that what matters most to children's status is likely to be the education of their parents, not the education of the household head and his spouse. The results of Model 2-2 replacing *lit_fat* by *hd_lit* and *lit_mot* by *sp_lit* are qualitatively the same as those of Model 2-1. The education level of the head and his wife reduce child labor and increase schooling, with a bigger impact from educated females in the household. However, the size of coefficients on *sp_lit* is smaller than that on *lit_mot* and the significance level of coefficients on *sp_lit* is lower than that on *lit_mot* in the $cl_2$ and *enrl* regressions. This suggests that the set of *lit_fat* and *lit_mot* may be superior to the set of *hd_lit* and *sp_lit* in explaining child labor and schooling.

To confirm this, in Model 2-3, we adopt specifications using all indicators of education, and test which of these variables can be eliminated. If the set of *lit_fat* and *lit_mot* are the determinants of child labor and schooling and the additional information included in the set of *hd_lit* and *sp_lit* in explaining them is negligible, it is expected that the null hypothesis that coefficients on *lit_fat* and *lit_mot* are zero is rejected but the null hypothesis that coefficients on *hd_lit* and *sp_lit* are zero is not rejected. The $\chi^2$ statistics reported in the table exactly show this pattern for all of the three regressions. Therefore, the test results are in favor of the education of parents.

These results give evidence to support the view that the parents' education is significantly associated with child labor and schooling while the household head and his/her spouse's education is not. Therefore, it is suggested that for those children belonging to the non-standard household type, what matters most to children's status is the education of their parents, not the education of the household head and his spouse. This finding, that the education level of the household head may not be the best indicator for household welfare, adds a new perspective to existing studies on the productivity of household enterprises in developing countries (Yang 1997a; 1997b; Jolliffe 2002; Laszlo 2005).

The finding seems less consistent with the social-planner-type unitary household approach, where the household head optimizes resource allocation within the household as a social planner or a dictator, so that the head's preference (and his/her education) affects child status directly, and is more consistent with non-unitary household models, where adult household members bargain over intrahousehold resource allocation. The parents of the child may have more bargaining power in determining child status than the household head and his wife. However, as discussed already, since education also affects the market and reservation wages of mothers and fathers, our results can also be seen as compatible with the unitary approach.

The above findings raise a question as to the nature of these households, in comparison with the standard type where the father of the child is the household head and the mother of the child is the head's spouse. There are 179 children, added in this subsection with complete household information, who belong to various types of joint families, including three-generation families with more than one couple of the second generation living together. Among these children, 67 are from typical extended families where the grandfather of the child is the household head and the father of the child is the eldest son of the head. Fifty children are from households where the child's father is absent and 40 children are from female-headed households in which the child's mother serves as the head (the number of children overlapping the two categories, i.e., households where the child's mother is the head and the child's father is absent, is 27). In addition to these, there are various kinds of demographic structures, most of which arise from three generations of the family living together. We attempted to create several dummy variables to represent some of the major types and added in the regressions. These additional variables are not significant (not reported).

C. *Robustness of the Regression Results*

The above findings were robustly found from different specifications,[10] except for changes due to specifications already mentioned. First, the education level of the parents of the child is measured by a continuous variable of schooling years, not by a literacy dummy. Second, specifications using a finer classification of communities based on caste names (20 categories) were attempted. These models yielded coefficients on household and individual characteristics that are very similar to those reported in this paper.

Third, the OLS results using linear probability models instead of logit models, are qualitatively the same as those reported in this paper. The size of the marginal effects of the explanatory variables on the probability is very close to those in this paper, as far as the statistically significant variables are concerned.

Fourth, instead of the dummy variables of working/enrolled, continuous variables of each child's time-use were calculated from the micro dataset (see Sawada *et al*. (2006) for detailed analysis of the child's time use). As far as the child's working hours or studying hours are regressed in a tobit model on the same list of variables included in the models of this paper, we obtain qualitatively the same results.[11] In the literature, because of the overlapping of working and studying and also because of the existence of "idle" children[12] whose usual activity is neither work nor study, some authors estimate multinomial logit models with a discrete variable of "work only," "work and study," "study only," and "idle" (Bacolod and Ranjan 2003; Deb and Rosati 2002). Given more detailed information on time use, these multinomial logit estimations are inefficient. It is better to analyze the continuous variables of time use, as has been done by Rosati and Rossi (2003) and Bhalotra and Heady (2003). The results reported in this paper are robust to this type of specification.

## V. CONCLUSION

This paper has empirically analyzed the determinants of child labor and school enrollment in rural Andhra Pradesh, India, through estimating a village fixed-effect logit model for each child. The results of the regressions first confirmed the previous, well-established results: parents' education is associated with less child labor and more school enrollment; richer households are more likely to send their children to school; and children in female-headed households are disadvantaged. Second, the results provide further evidence supporting the previous, nonestablished results: mothers' education matters more and is equally important for boys and girls while fathers' education matters less and, if it exists, is significant for boys only; the impact of land is insignificant on child labor in an environment where the impact of land holding on improving marginal returns of child labor in farm work is small, possibly as a result of drought. Third, the research has yielded previously unknown results: in households with multiple pairs of adults, what matters most is the education of the child's parents, not the education of the household head and his or her spouse; households belonging to scheduled castes, scheduled tribes, and the Muslim community are more likely to send their children to school than households belonging to "other backward classes."

Although tentative, these findings have several policy implications. The last finding may suggest that that policy interventions targeted at these communities are effective. Many of the findings are more consistent with predictions of collective household models where within-household bargaining plays an important role than with predictions of unitary household models where the household head is likely to be the sole decision maker. The results here are thus consistent with those reported by Sawada *et al*. (2006) and Fuwa *et al*. (2006b). This implies that in designing child labor eradication and school promotion policies, targeting mothers of current children is more important than focusing on household heads. Finally, a caveat of this paper is that the quantitative analysis is based on a reduced-form approach with only exogenous shifters as explanatory variables and a formal test of distinguishing unitary from collective household models is not attempted. See Sawada *et al*. (2006) and Fuwa *et al*. (2006b) for such attempts using the same micro data.

## FOOTNOTES

[1] Lieten (2002) also estimated the number of working children in India as more than 100 million and commented that this number is 10 times more than the official figures available from census and NSS reports.

[2] Elsewhere in the literature on the productivity of household enterprises in developing countries, the question whose education matters has been investigated intensively (e.g., Yang [1997a; 1997b]; Jolliffe [2002]; Laszlo [2005]).

[3] A related issue is whether the working/enrollment status of children belonging to nuclear families is different from that of children belonging to joint families. This issue has been analyzed by Edlund and Rahman (2005) and Ito (2005).

[4] The agro-ecological conditions in the study villages are similar to those in villages that were surveyed intensively during the 1970s and 1980s by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT).

[5] See Ravallion and Wodon (2000) for an analysis of work/school substitutability in the context of South Asia. They evaluated the impact of the enrollment subsidy on attendance and child work hours and found that there was a limited substitutability

between schooling and leisure, as schooling did not completely replace labor, implying a fall in leisure.

[6] Unitary household models can be derived from two different approaches. One is the dictator (social planner) models, where the household head optimizes resource allocation within the household as a social planner or a dictator. The other is the common preferences models where all adult members are assumed to have the same preferences. Under the social-planner-type unitary household approach, we expect that what matters most to the child's working status is the education of the household head.

[7] One concern is that measurement errors exist in land values, since we obtained this value from the question "if you are to sell the land, how much is it worth?"

[8] There are some variables characterizing the grandparents that were not statistically significant in all specifications in this paper. However, they were significant determinants in other aspects of household resource allocation such as time use of the children or households' consumption expenditure (see Fuwa *et al*. [2006b] and Sawada *et al*. [2006]). Therefore, to avoid the omitted variable bias, we preserve these insignificant variables in this paper.

[9] An exception in the existing empirical literature on India is a study by Luke and Munshi (2005), who found that in tea plantations, human capital investment in children by migrants is higher among lower caste households under quasi-experimental conditions. They attribute their finding to a network-based interpretation that low caste households have inferior home networks so that they invest more in children. Further study will be needed to examine whether this explanation holds in our sample as well.

[10] These results are available on request.

[11] Specifically, we used information collected in the one week time use module. The narrowly defined child work includes (i) remunerated work and (ii) non-remunerated work. The broadly defined child work is the sum of (i), (ii), (iii) household chores, and (iv) child care. Schooling time is as reported (see Sawada *et al*. 2006).

[12] These children are also called "nowhere" children in the Indian context (Lieten 2002; Venkatanarayana 2004).

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**TABLE 1**

Incidence of Child Labor in India among Children Aged 10–14 Years

| | All India | | | | | |
|---|---|---|---|---|---|---|
| | NSS 1993/94 | | | NSS 1999/2000 | | |
| | National | Rural | Urban | National | Rural | Urban |
| “$cl_1$” Market work* | 9.3 | 10.8 | 4.8 | 6.6 | 7.5 | 3.7 |
| “$cl_2 - cl_1$” Domestic work | 8.4 | 9.6 | 4.7 | 5.9 | 6.6 | 3.6 |
| Attend school | 71.2 | 66.8 | 72.8 | 75.8 | 72.8 | 84.9 |
| | Rural Bihar-UP LSMS 1997/98 | | | Rural AP Survey 2005 | | |
| | Total | Boys | Girls | Total | Boys | Girls |
| “$cl_1$” Market work* | 11.4 | 12.2 | 10.5 | 47.5 | 42.8 | 52.4 |
| “$cl_2 - cl_1$” Domestic work | 16.9 | 3.2 | 34.0 | 6.7 | 2.4 | 11.2 |
| Attend school | 68.4 | 79.9 | 54.1 | 38.0 | 44.9 | 30.7 |

Sources: Edmonds, Pavcnik, and Topalova (2005) for National Sample Survey (NSS) and Sakamoto (2006) for Living Standard Measurement Study (LSMS).
Note: For rural Andhra Pradesh (AP), weighted means are reported, which were corrected for the differences in sampling probabilities. UP, Uttar Pradesh.
* Market work includes works for household enterprise.

**TABLE 2**

Incidence of Child Labor in Rural Andhra Pradesh, 2005

(%)

| | Aged 5–9 Years | | | Aged 10–14 Years | | |
|---|---|---|---|---|---|---|
| | Total | Boys | Girls | Total | Boys | Girls |
| Number of observations | 393 | 197 | 196 | 607 | 312 | 295 |
| Percentage distribution of "most important occupation": | | | | | | |
| "$cl_1$" Market work* | | | | | | |
| Own farming | 0.98 | 0.23 | 1.68 | 10.77 | 8.92 | 12.73 |
| Tenant farming | 0.38 | 0.44 | 0.33 | 0.49 | 0.53 | 0.45 |
| Agricultural wage labor | 1.92 | 1.14 | 2.66 | 23.88 | 14.63 | 33.67 |
| Livestock work | 6.17 | 4.51 | 7.73 | 10.81 | 16.16 | 5.16 |
| Own household business | 0.20 | 0.00 | 0.38 | 1.30 | 2.28 | 0.27 |
| Employee of other's business | 0.00 | 0.00 | 0.00 | 0.22 | 0.29 | 0.15 |
| "$cl_2 - cl_1$" Domestic work | 2.96 | 0.33 | 5.44 | 6.70 | 2.40 | 11.24 |
| Student | 61.01 | 68.65 | 53.81 | 36.28 | 42.34 | 29.87 |
| Idle and others | | | | | | |
| Idle | 21.70 | 23.74 | 19.78 | 5.22 | 7.27 | 3.05 |
| Others | 4.69 | 0.96 | 8.19 | 4.32 | 5.18 | 3.41 |
| Currently enrolled in school | 63.11 | 69.37 | 57.22 | 37.99 | 44.89 | 30.70 |

Note: Weighted means are reported, which were corrected for the differences in sampling probabilities.
* Market work includes works for household enterprise.

**TABLE 3**

Summary Statistics of Variables Used in the Logit Regression

| Variable | NOB | Mean | SD | Min. | Max. |
|---|---|---|---|---|---|
| *Dependent variables:* | | | | | |
| $cl_1$ | 1,000 | 0.321 | dummy | 0 | 1 |
| $cl_2$ | 1,000 | 0.372 | dummy | 0 | 1 |
| *enrl* | 1,000 | 0.482 | dummy | 0 | 1 |
| *Explanatory variables:* | | | | | |
| Individual characteristics of the child: | | | | | |
| *age* | 1,000 | 10.072 | 2.674 | 5 | 14 |
| *sex* | 1,000 | 0.498 | dummy | 0 | 1 |
| Household or parental education: | | | | | |
| *lit_fat* | 1,000 | 0.281 | dummy | 0 | 1 |
| *lit_mot* | 1,000 | 0.073 | dummy | 0 | 1 |
| *hd_lit* | 1,000 | 0.289 | dummy | 0 | 1 |
| *sp_lit* | 1,000 | 0.070 | dummy | 0 | 1 |
| Demographic characteristics: | | | | | |
| *hd_sex* | 1,000 | 0.058 | dummy | 0 | 1 |
| *nonnucl* | 1,000 | 0.247 | dummy | 0 | 1 |
| *no_fat* | 1,000 | 0.100 | dummy | 0 | 1 |
| *no_mot* | 1,000 | 0.118 | dummy | 0 | 1 |
| *hhsize* | 1,000 | 8.301 | 4.656 | 3 | 29 |
| *infants* | 1,000 | 0.668 | 1.036 | 0 | 5 |
| *children* | 1,000 | 3.549 | 2.018 | 1 | 12 |
| *adeld* | 1,000 | 3.665 | 2.220 | 1 | 12 |
| Asset related information: | | | | | |
| *bplhold* | 1,000 | 0.748 | dummy | 0 | 1 |
| *asset* | 1,000 | 1.463 | 2.868 | 0 | 48.245 |
| *landval* | 1,000 | 0.988 | 2.713 | 0 | 48 |
| *asset_ag* | 1,000 | 0.029 | 0.088 | 0 | 1.7 |
| *asset_lv* | 1,000 | 0.106 | 0.176 | 0 | 4.04 |
| *asset_hh* | 1,000 | 0.340 | 0.423 | 0 | 7.02 |
| Grandparents' information: | | | | | |
| *hdf_lit* | 970 | 0.230 | dummy | 0 | 1 |
| *spf_lit* | 997 | 0.190 | dummy | 0 | 1 |
| *f_land* | 1,000 | 5.576 | 9.705 | 0 | 80 |
| *m_land* | 1,000 | 4.280 | 6.812 | 0 | 50 |
| *hdp_adiff* | 970 | 5.209 | 4.765 | 0 | 30 |
| *spp_adiff* | 983 | 4.745 | 4.594 | 0 | 25 |
| Community dummies: | | | | | |
| *SC* | 996 | 0.188 | dummy | 0 | 1 |
| *ST* | 996 | 0.065 | dummy | 0 | 1 |
| *UMH* | 996 | 0.029 | dummy | 0 | 1 |
| *Muslim* | 996 | 0.042 | dummy | 0 | 1 |

Note: The number of observations (NOB) is 1,000 (those children reported in Table 2) except for several variables with missing information. Weighted means and standard deviations (SD) are reported, which were corrected for the differences in sampling probabilities.

**TABLE 4**

Logit Regression Results (Children Belonging to the Standard-Type Households)

| | $cl_1$ | | $cl_2$ | | *enrl* | |
|---|---|---|---|---|---|---|
| | Coef. | $z$ | Coef. | $z$ | Coef. | $z$ |
| Model 1-1: Basic specifications | | | | | | |
| *age* | 0.900 | 3.36*** | 0.785 | 3.45*** | 0.184 | 1.23 |
| *age_squared* | – 0.028 | – 1.25 | – 0.015 | – 0.77 | – 0.054 | – 3.43*** |
| *sex* | 0.674 | 2.54** | 1.001 | 3.61*** | – 0.839 | – 3.39*** |
| *lit_fat* | – 0.859 | – 2.13** | – 0.688 | – 1.65* | 0.515 | 1.52 |
| *lit_fat*sex* | – 0.093 | – 0.17 | 1.039 | 1.95* | – 0.616 | – 1.34 |
| *lit_mot* | – 2.310 | – 2.70*** | – 2.459 | – 3.00*** | 2.426 | 3.74*** |
| *lit_mot*sex* | – 0.063 | – 0.05 | 0.455 | 0.45 | – 0.080 | – 0.09 |
| *hhsize* | – 0.006 | – 0.16 | – 0.018 | – 0.47 | – 0.029 | – 0.84 |
| *bplhold* | 0.230 | 0.71 | 0.146 | 0.47 | 0.660 | 2.27** |
| *asset* | – 0.000 | 0.00 | – 0.011 | – 0.35 | 0.082 | 1.38 |
| *SC* | – 0.818 | – 2.83*** | – 0.653 | – 2.09** | 0.441 | 1.56 |
| *ST* | – 1.205 | – 1.10 | – 0.998 | – 0.95 | 1.241 | 1.58 |
| *UMH* | – 1.412 | – 1.77* | – 2.028 | – 2.86*** | 1.967 | 2.92*** |
| *Muslim* | – 2.132 | – 2.78*** | – 1.125 | – 1.88* | 1.141 | 2.12** |
| Effective NOB | | 729 | | 729 | | 745 |
| Wald $\chi^2$ for zero slopes | | 149.69*** | | 154.87*** | | 138.23*** |
| Pseudo $R^2$ | | 0.3266 | | 0.3342 | | 0.2316 |
| Model 1-2: Specifications disaggregating asset into four sources | | | | | | |
| *age* | 0.896 | 3.38*** | 0.781 | 3.53*** | 0.182 | 1.21 |
| *age_squared* | – 0.027 | – 1.23 | – 0.015 | – 0.74 | – 0.054 | – 3.41*** |
| *sex* | 0.658 | 2.47** | 0.976 | 3.52*** | – 0.842 | – 3.41*** |
| *lit_fat* | – 0.881 | – 2.17** | – 0.782 | – 1.86* | 0.482 | 1.40 |
| *lit_fat*sex* | – 0.038 | – 0.07 | 1.090 | 2.03** | – 0.657 | – 1.41 |
| *lit_mot* | – 2.340 | – 2.74*** | – 2.510 | – 3.04*** | 2.453 | 3.78*** |
| *lit_mot*sex* | 0.005 | 0.00 | 0.609 | 0.60 | – 0.081 | – 0.10 |
| *hhsize* | – 0.005 | – 0.14 | – 0.025 | – 0.63 | – 0.033 | – 0.96 |
| *bplhold* | 0.203 | 0.63 | 0.103 | 0.34 | 0.643 | 2.21** |
| *landval* | 0.012 | 0.32 | – 0.015 | – 0.49 | 0.061 | 1.56 |
| *asset_ag* | 0.998 | 0.95 | 1.817 | 1.53 | – 0.571 | – 0.55 |
| *asset_lv* | 0.334 | 0.46 | 0.788 | 0.88 | 0.515 | 0.80 |
| *asset_hh* | – 0.332 | – 1.24 | – 0.231 | – 0.89 | 0.235 | 0.97 |
| *SC* | – 0.829 | – 2.85*** | – 0.633 | – 2.02** | 0.459 | 1.61 |
| *ST* | – 1.280 | – 1.13 | – 1.212 | – 1.11 | 1.102 | 1.37 |
| *UMH* | – 1.389 | – 1.74* | – 2.007 | – 2.81*** | 1.996 | 2.97*** |
| *Muslim* | – 2.171 | – 2.89*** | – 1.176 | – 2.05** | 1.164 | 2.15** |
| Effective NOB | | 729 | | 729 | | 745 |
| Wald $\chi^2$ for zero slopes | | 150.16*** | | 154.60*** | | 140.21*** |
| Pseudo $R^2$ | | 0.3290 | | 0.3384 | | 0.2333 |
| $\chi^2(3)$ test: | | | | | | |
| $H_0$ = Model 1-1 | | 2.29 n.s. | | 3.98 n.s. | | 1.37 n.s. |

**Table 4** (Continued)

| | *$cl_1$* | | *$cl_2$* | | *enrl* | |
|---|---|---|---|---|---|---|
| | Coef. | *z* | Coef. | *z* | Coef. | *z* |
| Model 1-3: Specifications disaggregating *hhsize* demographically | | | | | | |
| *age* | 0.897 | 3.34*** | 0.785 | 3.45*** | 0.178 | 1.19 |
| *age_squared* | – 0.028 | – 1.26 | – 0.015 | – 0.76 | – 0.055 | – 3.51*** |
| *sex* | 0.693 | 2.59*** | 0.999 | 3.58*** | – 0.817 | – 3.29*** |
| *lit_fat* | – 0.856 | – 2.10** | – 0.691 | – 1.65* | 0.555 | 1.62 |
| *lit_fat*sex* | – 0.097 | – 0.18 | 1.052 | 1.98** | – 0.634 | – 1.39 |
| *lit_mot* | – 2.332 | – 2.72*** | – 2.445 | – 2.99*** | 2.351 | 3.58*** |
| *lit_mot*sex* | – 0.085 | – 0.07 | 0.454 | 0.45 | – 0.110 | – 0.13 |
| *infants* | – 0.028 | – 0.18 | 0.032 | 0.20 | – 0.076 | – 0.54 |
| *children* | – 0.045 | – 0.60 | – 0.027 | – 0.33 | – 0.112 | – 1.51 |
| *adeld* | 0.024 | 0.29 | – 0.031 | – 0.37 | 0.092 | 1.16 |
| *bplhold* | 0.244 | 0.76 | 0.143 | 0.47 | 0.675 | 2.29** |
| *asset* | – 0.002 | – 0.04 | – 0.011 | – 0.36 | 0.066 | 1.47 |
| *SC* | – 0.826 | – 2.85*** | – 0.647 | – 2.05** | 0.421 | 1.46 |
| *ST* | – 1.164 | – 1.06 | – 0.967 | – 0.92 | 1.312 | 1.68* |
| *UMH* | – 1.410 | – 1.77* | – 2.029 | – 2.85*** | 2.046 | 3.03*** |
| *Muslim* | – 2.126 | – 2.76*** | – 1.120 | – 1.86* | 1.212 | 2.22** |
| Effective NOB | | 729 | | 729 | | 745 |
| Wald $\chi^2$ for zero slopes | | 151.48*** | | 156.02*** | | 142.70*** |
| Pseudo $R^2$ | | 0.3271 | | 0.3344 | | 0.2344 |
| $\chi^2(2)$ test | | 0.31 n.s. | | 0.10 n.s. | | 2.78 n.s. |
| Model 1-4: Specifications with additional variables characterizing non-coresident grandparents | | | | | | |
| *age* | 0.863 | 3.21*** | 0.721 | 3.24*** | 0.247 | 1.58 |
| *age_squared* | – 0.024 | – 1.07 | – 0.008 | – 0.43 | – 0.066 | – 3.95*** |
| *sex* | 0.764 | 2.79*** | 1.095 | 3.80*** | – 0.953 | – 3.65*** |
| *lit_fat* | – 0.797 | – 1.81* | – 0.574 | – 1.31 | 0.258 | 0.71 |
| *lit_fat*sex* | – 0.137 | – 0.24 | 0.982 | 1.80* | – 0.799 | – 1.70* |
| *lit_mot* | – 2.204 | – 2.33** | – 2.298 | – 2.58** | 2.499 | 3.04*** |
| *lit_mot*sex* | 0.039 | 0.03 | 0.738 | 0.69 | – 0.545 | – 0.51 |
| *hhsize* | – 0.019 | – 0.47 | – 0.030 | – 0.71 | – 0.027 | – 0.78 |
| *bplhold* | 0.076 | 0.23 | 0.070 | 0.22 | 0.842 | 2.56** |
| *asset* | 0.007 | 0.16 | 0.000 | 0.00 | 0.112 | 1.45 |
| *hdf_lit* | – 0.357 | – 1.10 | 0.087 | 0.29 | 0.705 | 2.15** |
| *spf_lit* | – 0.149 | – 0.42 | – 0.546 | – 1.64* | 0.654 | 2.15** |
| *f_land* | – 0.017 | – 1.04 | – 0.013 | – 0.73 | 0.014 | 0.78 |
| *m_land* | 0.027 | 1.56 | 0.019 | 0.98 | – 0.024 | – 1.27 |
| *hdp_adiff* | – 0.021 | – 0.61 | – 0.008 | – 0.25 | 0.049 | 1.61 |
| *spp_adiff* | 0.021 | 0.60 | – 0.010 | – 0.27 | 0.023 | 0.74 |
| *SC* | – 0.749 | – 2.44** | – 0.714 | – 2.07** | 0.632 | 1.95* |
| *ST* | – 1.253 | – 1.09 | – 0.968 | – 0.90 | 1.528 | 1.73* |
| *UMH* | – 0.963 | – 1.04 | – 1.621 | – 2.04** | 1.542 | 2.17** |
| *Muslim* | – 2.218 | – 2.79*** | – 1.306 | – 2.19** | 1.472 | 2.65*** |
| Effective NOB | | 690 | | 690 | | 702 |
| Wald $\chi^2$ for zero slopes | | 142.03*** | | 157.24*** | | 135.38*** |
| Pseudo $R^2$ | | 0.3323 | | 0.3384 | | 0.2715 |
| $\chi^2(6)$ test | | 5.71 n.s. | | 4.12 n.s. | | 14.43** |

Notes:
1. The total number of observations (NOB) used in the regression is 761. Due to “perfect” prediction by several fixed effects, the effective NOB is sometimes smaller than 761.
2. All models are estimated by equation-by-equation weighted logit with village fixed effects. The weighted estimation method was adopted to correct for the differences in sampling probabilities. The village fixed effects were jointly significant at the 1% level.
3. In $\chi^2(k)$ tests, the null hypothesis is Model 1-1.
***, **, and * represent statistically significance at the 1%, 5%, and 10% level, respectively.

**TABLE 5**
Logit Regression Results (Using All Children in the Sample)

| | $cl_1$ | | $cl_2$ | | *enrl* | |
|---|---|---|---|---|---|---|
| | Coef. | *z* | Coef. | *z* | Coef. | *z* |
| Model 2-1: Specifications using parents' education | | | | | | |
| *age* | 0.882 | 3.68*** | 0.798 | 3.79*** | 0.121 | 0.94 |
| *age_squared* | – 0.031 | – 1.50 | – 0.021 | – 1.15 | – 0.044 | – 3.23*** |
| *sex* | 0.661 | 2.93*** | 0.956 | 4.09*** | – 0.749 | – 3.62*** |
| *lit_fat* | – 1.129 | – 2.97*** | – 0.892 | – 2.35** | 0.642 | 2.21** |
| *lit_fat*sex* | – 0.008 | – 0.02 | 0.823 | 1.76* | – 0.394 | – 1.01 |
| *lit_mot* | – 2.110 | – 2.52** | – 2.291 | – 2.98*** | 1.743 | 2.60*** |
| *lit_mot*sex* | – 0.568 | – 0.48 | 0.198 | 0.21 | 0.577 | 0.68 |
| *hd_sex* | 0.723 | 1.24 | 0.705 | 1.13 | – 1.391 | – 2.79*** |
| *nonnucl* | – 1.053 | – 2.36** | – 0.815 | – 1.89* | 0.930 | 2.77*** |
| *no_fat* | – 0.144 | – 0.30 | – 0.350 | – 0.71 | 0.032 | 0.07 |
| *no_mot* | 0.723 | 1.21 | 0.675 | 1.12 | – 0.810 | – 1.58 |
| *hhsize* | – 0.051 | – 1.52 | – 0.062 | – 1.70* | – 0.013 | – 0.46 |
| *bplhold* | 0.287 | 1.02 | 0.184 | 0.69 | 0.714 | 3.03*** |
| *asset* | 0.039 | 1.14 | 0.033 | 0.97 | 0.019 | 0.74 |
| *SC* | – 0.706 | – 2.82*** | – 0.574 | – 2.20** | 0.361 | 1.47 |
| *ST* | – 1.122 | – 1.26 | – 0.248 | – 0.28 | 0.297 | 0.46 |
| *UMH* | – 1.272 | – 1.98** | – 1.397 | – 2.44** | 1.642 | 3.21*** |
| *Muslim* | – 1.703 | – 2.66*** | – 0.842 | – 1.56 | 1.190 | 2.39** |
| Effective NOB | | 996 | | 996 | | 974 |
| Wald $\chi^2$ for zero slopes | | 191.58*** | | 203.54*** | | 150.07*** |
| Pseudo $R^2$ | | 0.3191 | | 0.3209 | | 0.2149 |
| Model 2-2: Specifications using the education of the household head and his/her spouse | | | | | | |
| *age* | 0.917 | 3.77*** | 0.815 | 3.86*** | 0.099 | 0.77 |
| *age_squared* | – 0.033 | – 1.61 | – 0.023 | – 1.22 | – 0.042 | – 3.13*** |
| *sex* | 0.682 | 2.95*** | 0.907 | 3.86*** | – 0.691 | – 3.31*** |
| *hd_lit* | – 1.092 | – 3.12*** | – 1.100 | – 3.02*** | 0.967 | 3.11*** |
| *hd_lit*sex* | – 0.114 | – 0.24 | 0.958 | 2.02** | – 0.631 | – 1.50 |
| *sp_lit* | – 2.115 | – 2.63*** | – 1.108 | – 1.76* | 0.995 | 1.99** |
| *sp_litr*sex* | – 0.260 | – 0.23 | – 0.742 | – 0.88 | 1.018 | 1.44 |
| *hd_sex* | 0.056 | 0.11 | 0.094 | 0.17 | – 1.079 | – 2.17** |
| *nonnucl* | – 0.902 | – 2.59** | – 0.898 | – 2.59** | 0.669 | 2.51** |
| *no_fat* | dropped | | dropped | | – 1.366 | – 0.98 |
| *no_mot* | 0.546 | 1.23 | 0.568 | 1.26 | 0.018 | 0.05 |
| *hhsize* | – 0.049 | – 1.49 | – 0.052 | – 1.50 | – 0.006 | – 0.22 |
| *bplhold* | 0.189 | 0.69 | 0.118 | 0.45 | 0.748 | 3.14*** |
| *asset* | 0.064 | 1.50 | 0.047 | 1.23 | 0.003 | 0.12 |
| *SC* | – 0.714 | – 2.89*** | – 0.567 | – 2.20** | 0.402 | 1.66* |
| *ST* | – 1.048 | – 1.16 | – 0.015 | – 0.02 | 0.128 | 0.20 |
| *UMH* | – 1.452 | – 2.29** | – 1.569 | – 2.87*** | 1.817 | 3.57*** |
| *Muslim* | – 1.705 | – 2.80*** | – 0.845 | – 1.58 | 1.246 | 2.51** |
| Effective NOB | | 994 | | 994 | | 974 |
| Wald $\chi^2$ for zero slopes | | 188.46*** | | 198.31*** | | 151.43*** |
| Pseudo $R^2$ | | 0.3166 | | 0.315 | | 0.2074 |

**TABLE 5** (Continued)

| | $cl_1$ | | $cl_2$ | | *enrl* | |
|---|---|---|---|---|---|---|
| | Coef. | *z* | Coef. | *z* | Coef. | *z* |
| Model 2-3: Specifications using both groups of education variables | | | | | | |
| *age* | 0.890 | 3.73*** | 0.787 | 3.79*** | 0.125 | 0.96 |
| *age_squared* | – 0.031 | – 1.51 | – 0.019 | – 1.04 | – 0.045 | – 3.33*** |
| *sex* | 0.661 | 3.32*** | 0.917 | 3.89*** | – 0.836 | – 4.71*** |
| *lit_fat* | – 0.725 | – 1.48 | – 0.255 | – 0.33 | 0.058 | 0.14 |
| *lit_fat*sex* | | | 0.023 | 0.02 | | |
| *lit_mot* | – 1.882 | – 2.71*** | – 3.068 | – 2.98*** | 2.453 | 2.48** |
| *hd_lit* | – 0.476 | – 0.98 | – 0.786 | – 1.08 | 0.490 | 1.21 |
| *hd_lit*sex* | | | 0.971 | 1.06 | | |
| *sp_lit* | – 0.581 | – 0.84 | 1.016 | 1.00 | – 0.456 | – 0.51 |
| *hd_sex* | 0.231 | 0.46 | 0.285 | 0.55 | – 1.055 | – 2.32** |
| *nonnucl* | – 1.067 | – 2.57** | – 0.915 | – 2.19** | 0.699 | 2.20** |
| *no_fat* | – 0.249 | – 0.46 | – 0.484 | – 0.88 | – 0.198 | – 0.44 |
| *no_mot* | 0.773 | 1.50 | 0.789 | 1.46 | 0.089 | 0.22 |
| *hhsize* | – 0.048 | – 1.44 | – 0.057 | – 1.58 | – 0.006 | – 0.22 |
| *bplhold* | 0.212 | 0.77 | 0.122 | 0.47 | 0.719 | 3.05*** |
| *asset* | 0.054 | 1.39 | 0.042 | 1.09 | 0.012 | 0.46 |
| *SC* | – 0.715 | – 2.85*** | – 0.563 | – 2.14** | 0.375 | 1.54 |
| *ST* | – 1.136 | – 1.24 | – 0.417 | – 0.49 | 0.350 | 0.56 |
| *UMH* | – 1.402 | – 2.19** | – 1.485 | – 2.66*** | 1.739 | 3.32*** |
| *Muslim* | – 1.701 | – 2.68*** | – 0.832 | – 1.52 | 1.241 | 2.45** |
| Effective NOB | | 996 | | 996 | | 974 |
| Wald $\chi^2$ for zero slopes | | 194.72*** | | 207.70*** | | 147.61*** |
| Pseudo $R^2$ | | 0.3216 | | 0.3250 | | 0.2132 |
| $\chi^2(k)$: parents† | | 9.69*** | | 9.26** | | 6.16** |
| $\chi^2(k)$: head and spouse† | | 1.80 n.s. | | 2.72 n.s. | | 1.88 n.s. |

Notes:

1. The total number of observations (NOB) used in the regression is 1,000. Due to "perfect" prediction by several fixed effects, the effective NOB is sometimes smaller than 1,000.
2. All models are estimated by equation-by-equation weighted logit with village fixed effects. The weighted estimation method was adopted to correct for the differences in sampling probabilities. The village fixed effects were jointly significant at the 1% level.

***, **, and * represent statistically significance at the 1%, 5%, and 10% level, respectively.

† "$\chi^2$ ($k$): parents" tests all coefficients on parents' education = 0. "$\chi^2$ ($k$): head and spouse" tests all coefficients on head and spouses' education = 0. $k$ = 2 for $cl_1$ and *enrl*, $k$ = 3 for $cl_2$.