Whose Education Matters for Child Labor and School Enrollment?
A Case of Rural Andhra Pradesh, India

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Abstract: 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 extended 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

High incidence of child labor and staggering school enrollment of children continue to be a serious problem facing India. According to ILO-IPEC [2005], about 127 million children in the age group 5-14 are engaged in work, of which more than 100 million are attributed to India alone.[1] There have been a number of attempts to eradicate child labor and to send children to school in India, such as legal actions against child labor, trade sanctions, enlightenment of parents, education subsidies, etc. Nevertheless, the impact of these policies has been limited, judging from the current estimates of the number of working children. Similarly to the limited policy success, the understanding of the determinants of child labor is also limited, though the number of theoretical and empirical work on child labor has been 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 (e.g., Aggarwal [2004], Basu, Das, and Dutta [2003], Deb and Rosati [2002], Edmonds, Pavcnik, and Topalova [2005], Sakamoto [2006]). These studies have one thing in common: they employ datasets collected by a large-scale sample household survey conducted by national or international agencies. In other words, the analysts of these papers were seldom involved in the design and implementation of the survey. This limits their analysis into the one using information available in the standardized household questionnaire only. There may be some empirical studies, especially from sociology or anthropology background, which analyze child labor and school enrollment based on a detailed village survey. The findings from such studies cannot directly contribute to the understanding of the microeconomic mechanism of the child status. Since the incidence of child labor and school enrollment is a result of households' decision making, we believe that it is critically important to analyze the incidence as an issue of intrahousehold resource allocation within a household (Ito et al. [2006]).

With this belief, we conducted a special household survey in rural Andhra Pradesh to collect detailed information on intrahousehold resource allocation (Ito et al. [2006]). The rich information thus collected and the authors' close involvement in the survey distinguishes the analysis of this paper from those by others mentioned above. Methodologically, we follow the approach typically adopted in the existing studies on child labor using cross-section data: a

[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.

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. As a unique feature of this study, we focus on a previously unanswered question: Whose education matters most in deciding child labor and school enrollment? Most studies mentioned above are 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 to represent the education level of the guardians of the child. This paper extends the analysis to children belonging to households of other types 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 whose education matters in the context of child labor.[2] The extension is also practically important in India because of the prevalence of extended family system.[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 of 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 mandals (administrative blocks) in Kurnool District, Andhra Pradesh. Study villages and sample households were chosen randomly, with higher percentage of sampling for households with child labor (see Ito et al. [2006] for the sampling ratios). The study villages are remote from cities and dependent on both irrigated and unirrigated agriculture.[4] The appendix of Ito (ed.) [2005] reports the questionnaires that were

[2] Elsewhere in the literature on the productivity of household enterprises in developing countries, the question whose education matters has been investigated intensively (see e.g., Yang [1997a], [1997b], Jolliffe [2002], Laszlo [2006]).

[3] A related issue is whether the working/enrollment status of children belonging to nuclear families is different from that of children belonging to extended 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 villages that were surveyed

used by local collaborators/investigators for this survey.

In order to define child labor, we need to clarify the definitions of "child" and "work." Yet, this is quite difficult. First, the concept of child differs greatly across societies and cultural settings. In western societies, it is customary to define child by chronological age, but in many societies cultural and social factors enter as well. Second, the concept of work cannot be defined easily. There are different activities in which children are engaged. Children can help with domestic work, work in the farm or the household enterprise, or participate in labor market. It is not straightforward to draw a clear line between work and non-work child activities. A key question is whether the arrangement is "exploitative." In the extreme, it 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]).

Considering these difficulties, the incidence of child labor and child's enrollment in school is defined in this paper by a child's usual economic activity. Borrowing the classification in the ILO standards, we cover children in the age group 5-14. Not only wage works but also works inside the household without payment on the household's 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 have a consensus whether we should include household chores such as cleaning, water fetching, baby care-taking, etc. In this paper, we call such work "domestic work" and employ both a narrower definition of child labor (labeled cl_1) that includes only the market work and a wider definition of child labor (labeled cl_2) that includes both the market work and the domestic work. Since the most important activity that competes with work time for a child's time endowment is schooling, another variables labeled *enrl* is calculated. This is a dummy variable that takes 1 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 NSS (National Sample Survey) or LSMS (Living Standard Measurement Study) datasets, full information on detailed activities may not be available on smaller children. For instance, in the LSMS survey conducted in Bihar and Uttar Pradesh (henceforth "the UP-Bihar LSMS"), younger children aged 9 or less are asked about their usual status with a different list. Therefore, Table 1 reports the incidence ratio for children aged 10-14 (middle school age). At the all India level (NSS dataset), the incidence

intensively during the 1970s and 1980s by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT).

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. The decline was observed in both rural and urban areas. The school enrollment ratio increased instead 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 17% if the wider definition is used. The UP-Bihar LSMS data show a huge difference between boys and girls. The incidence of domestic work is high among girls so that their school enrollment ratio for girls is only 54% against 80% for boys.

Our dataset shows gender disparity similar to the one 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 our careful examination of children's activities in the field. We suspect that in NSS or LSMS, those households working mostly inside the house are labeled as doing domestic work regardless of their actual activity. Our observations in the fields suggest that most of the works done by these children are related with market activities such as processing of farm products and caretaking of livestock animals. Another possibility is that the difference reflects that people in Bihar and UP are more conservative to female works than the southern states so that female wage work is less prevalent in Bihar and UP than in South, given income levels (Aggarwal [2004]). The second difference is the level of child labor, which is much higher in our dataset than in UP-Bihar or NSS datasets. This reflects our sample design that we surveyed regions with more concentration of child labor and the sampling ratio is higher among those households with child labor than those without (see Ito [2006]).

Table 2 reports more details of children's activities as well as the information for younger children aged 5-9 (primary school age). Agricultural wage labor is the dominant workplace for elder children, followed by own farming and livestock work. For younger children, the child labor incidence is lower than for elder children but still as high as 8.9% (cl_1) and 11.7% (cl_1). Among younger children, livestock work is the most important work, followed by domestic work and agricultural wage labor. Thus, ignoring child labor among younger children brings a serious bias in any study on child labor and intrahousehold resource allocation in India. It is of interest that the school enrollment ratio in Table 2 is larger than the ratio of children who is reported as "student" as his/her usual status. The difference is explained by those children both working and studying but working as their main activity.

Fortunately, our dataset allows much detailed analysis of the coexistence of work and study for a single child, because we have collected detailed information on time use of each child.

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

III. Empirical Models

III.1. Empirical Strategy

We assume that the status of each child *i* is decided either by the household unitarily or by the guardians of the child inside the household through a collective bargaining process (see Ito et al. [2006] for the short survey and examples of these household models). We acknowledge that the education of a child is both investment for the future and the current consumption (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 faced by the household, and the preferences of the household. When a household is poor, its child is 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, 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 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* (school enrollment dummy for child *i*). Since child labor and schooling are usually regarded as substitutes, we expect the patterns of coefficients in the *enrol* regression are opposite to those in the cl_{1i} and cl_{2i} regressions. But how exact is the contrast? By looking at 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. As 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.

III.2. Empirical Models for Children in the Standard Type Households

We first estimate models using the subset of children aged 5-14 whose father is the household head and whose mother is the spouse of the household head. 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 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):

<u>(1) Individual characteristics of a child</u>: *age*, *age_squared* (defined as $(age\text{-}5)^2$, to capture non-lineairty of the age effect), and *sex* (a dummy for a girl).

<u>(2) Household characteristics</u>: *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 *mot_fat*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

[5] See Ravallion and Wodon (2000) for an analysis of wok/school substitutability in the context of South Asia. They evaluated the impact of its 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

in lakh Rs.), and dummy variables for the community (religion and wider caste groupings) of the household.

The cross terms *lit_fat*sex* and *mot_fat*sex* are included to investigate one aspect of the question whose education matters. If mothers' education is more important to girls and fathers' education is more important to boys in reducing child labor and in increasing school enrollment, we expect *lit_fat*sex* and *mot_fat*sex* to have the opposite signs (Thomas [1994], Quisumbing and Maluccio [2003]). Variable *bplhold* is a proxy for the government's labeling 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. 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 castes" (*OBC*). In India, it is often claimed that SC and ST are backward strata with lower interests in education. If this is correct, we expect coefficients on *SC* and *ST* are positive on cl_{1i} (cl_{2i}) and negative on *enrl*. We will examine whether this holds even 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.

<u>(3) Village fixed effects</u>: these collectively control for differences in market conditions, environments, 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 cart), *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 treatment by family labor, a larger size of livestock implies that the marginal returns to child labor on livestock increases, thus, leading to an increase of child labor, canceling out the child-labor-reduction effect of livestock as the source of wealth (Dreze and Kingdon [2001]). The land asset also has a similar characteristic

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replace labor, implying leisure to have fallen.

(Bhalotra and Heady [2003]). We can test whether each source of assets has a different impact by a χ^2 test for the null hypothesis that all coefficients on *landval*, *asset_ag*, *asset_lv*, and *asset_hh* are the same. As robustness check, we also estimate models with *landval* replaced by the acreages of irrigated and unirrigated plots.

In Model 1-3, *hhsize* is decomposed demographically: *infants* (the number of household members in the age group 0-4, *children* (the number of household members in the age group 5-14), and *adeld* (the number of household members aged 15 or older). The motivation of this extension is to examine the hypothesis that the 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 care-taking, we expect *infants* to have a positive effect on cl_{2i} (but not on cl_{1i}) (Basu, Das, and Dutta [2003], Rosati and Rossi [2003]). The positive effect of *infants* on cl_{2i} may be larger on girls than on boys, which we can test by the significance of the coefficient on the cross term *infants*sex*. In 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 χ^2 test for the null hypothesis that all coefficients on *infants*, *children*, and *adeld* are the same.

In Model 1-4, additional variables are included, which characterize the parents of the parents. Many of them are dead already or live separately from the current household (note that we limit the analysis to the children that 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 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 the parents' parents 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 significance of any grandparental variables does not rule out preference-based explanations consistent with unitary models if certain traits or preference 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.

Concretely, the additional variables include: *hdf_lit* (literacy of father's father), *spf_lit* (literacy of mother's father), *f_land* (land holding of father's father, with an acre of dry land weighted as a half acre of irrigated land), *m_land* (land holding of mother's father), *hdp_adiff* (the age difference of the father's parents), and *spp_adiff* (the age difference of the mother's parents). Though we have information on the literacy of father's mother and mother's mother, these two 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 χ^2 test for the null hypothesis that all coefficients on these variables are zero.

III.3. Empirical Models for All Children

In models using data on all children, two issues are investigated. The first is the effect of household type on child labor. In Model 2-1, the variables similar to those in Model 1-1 are employed. When we expand the sample, we face several observations where *not both* of the parents of a child are included in the household (e.g., either of the parents is dead or permanently absent). To exploit full information of the 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 parents' variables is missing and then created a dummy variable for the incomplete parents (*no_fat* and *no_mot*). In addition, we compile the 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 in the empirical context that various family types co-exist in India. For those children belonging to extended families, what matters for the child's status may not be a decision by his/her own parents, but a decision by the household head.[6] If this is true, the correct measures of the guardians' education are not *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

[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 what matters most to the child's working status is the education of the household head.

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 [2006]). These studies found that the education level of the household head may not be the best indicator. In contrast, such investigation has 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 groups of guardians' 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 χ^2 tests, we can examine 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 for brevity. The coefficients on the community dummies (*SC*, *ST*, *UMH*, and *Muslim*) are reported with *OBC* as the reference.

IV.1 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 a 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 economically 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 be 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 found a similar result (Aggarwal [2004], Basu, Das, and Dutta [2003], Deb and Rosati [2002], Dr`eze 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 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 education. This may seem readily consistent with the bargaining hypotheses under non-unitary household models: mothers prefer more education for children than fathers and mothers’ bargaining power is increased by 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 (e.g., through helping their homework at home) than are fathers. In any case, the finding that mother's education matters more than father's is supported by all specifications all of Models 1-1 to 2-3. The difference between the father’s and the mother’s education was found in South Asia, in studies by Dr`eze and Kingdon [2001], Rosati and Rossi [2003], and Sakamoto [2006]. However, their gender contrast is less 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 on girls. The canceling impact shown by the cross term is statistically significant on cl_2. Therefore, our data show that the father’s favor mostly goes to boys, not 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 the coefficient is statistically significant. Therefore, the regression results show that the mother’s favor goes equally to boys and girls. This finding is similar to the one reported by Quisumbing and Maluccio [2004], though our results are clearer than theirs.

Fifth, the household demographic size (*hhsize*) has an imprecisely estimated coefficient, unlike the finding by Ray [2000] that the 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 1-5). 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 the future births when deciding on elder siblings’ schooling, then adding elder siblings’ working status can separate 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 decompose in Model 1-3 *hhsize* into *infants* (the number of household members aged 4 or less), *children* (the number of household members aged 5-14), and *adeld* (others). The results show that the null hypothesis that these three have the same coefficient is not rejected in the child labor regressions while it is rejected at the 5% level in the *enrl* regression. In the *enrl* regression, the coefficient on *infants* is negative and that on *adeld* is positive, suggesting that children with younger siblings (more adults) are less (more) likely to go to school. The childcare explanation seems to explain the first one, as well as the positive sign of the coefficient on *infants* in the cl_2 regression, though the latter is not statistically significant. Thus, our results are consistent with findings by Basu, Das, and Dutta [2003] and Rosati and Rossi [2003] but less clearer than theirs. 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 insignificant coefficient on child labor while it has marginally significantly positive 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, the negative coefficients are mostly insignificant on child labor, while the positive effect on school enrollment is statistically significant. Thus the wealth impact is stronger on school enrollment but it is not discernible on reducing child labor. In other words, child labor is found to be almost constant over the (sampled) support of wealth distribution, holding other variables fixed. This indicates low wealth level, conditional on other covariates, is not a sufficient condition of child labor. This seems consistent with the MVF's claim that poverty is not THE determinant of child labor.

If we disaggregate the wealth into four sources (Model 1-2), the results do not change much: they are insignificant on child labor but some of them are significantly positive on school enrollment. Interestingly, the impact of *landval* on school enrollment is significantly positive, 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 rainfed and irrigated plots and the IV estimation using the acreage of both rainfed and irrigated plots as identifying IVs for *landval* yielded similar results: the land variables are not significant in explaining child labor while their impact on school enrollment is positive. Thus, the finding of this paper is robust. It is suggested that the productivity effect through family labor when the wealth takes the form of land may not be large in our case so that the land ownership leads to less child work and more schooling in our sample. This is against the finding by Bhalotra and Heady [2003] that the land ownership leads to more child work in Pakistan but consistent with the finding by Deb and Rosati [2002] that children of landless households are more likely to work in India. One possibility is that our survey was conducted in a drought year, resulting in smaller productivity effect through family labor when the wealth takes the form of land. The effect of livestock in our sample is insignificant in contrast to the finding by Dreze and Kingdon [2001] that livestock wealth decreases the school enrollment in India. The difference of the findings could be attributed to the smaller importance of dairy livestock activities in the study region than in North India.

Eighth, the results for Model 1-4 show that some of the characteristics of the parents' parents (proxy for EEPs) are statistically significant. For instance, *f_land* (land holding of father's father) decreases child labor cl_1, while *spf_lit* (mother's father's literacy) decreases both types of child labor and increases school enrollment. The χ^2 statistics to test the null hypothesis that all coefficients on these EEPs are zero show that the null is rejected. Therefore, we obtain evidence, although not very strong on the child labor regressions, that these proxies for EEPs do affect the child status, the evidence rejecting the unitary household approach (see other papers in this issue). This argument is valid if these variables represent EEPs only. For instance, the results show that mother's father's literacy 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

[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?"

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 send children less to work than households belonging to other backward castes. 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 send children more to school than households belonging to other backward castes. These effects for the upper and medium castes are as expected since these castes are regarded as socially advanced in the Indian rural setting. However, the signs of the coefficients on SC and Muslim dummies are opposite to the expectation and findings by Deb and Rosati [2002], Dreze and Kingdon [2001], Aggarwal [2004], and Sakamoto [2006]. Though not significant in several cases, the signs of the coefficients on *ST* also suggest that the welfare of ST children is better than that of other-backward-castes children. These households are more eager to schooling and more averse to child labor than "other backward castes." This may reflect the impact of civil movements in rural Andhra Pradesh to lift up the social conditions of SC, ST, and Muslim households.

IV.2 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 households that are not of the standard type (i.e., 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. More elderly children are more likely to work, girls are more likely to work and less likely to go to school, the education level of parents reduce child labor and increase schooling, with a bigger impact from the mother's education, and the status of ratio card holders and the asset level increase schooling. Thus the findings shown in the previous subsection are robust.

Second, the female headed households are more likely to send their children to work and less to school. This is a confirmation of previous studies in India (Aggarwal [2004]). However, the effect on child labor is small and statistically insignificant, while that on schooling is only marginally significant. Therefore, asymmetric effects are found, suggesting that child labor and schooling are not perfect substitute (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 more to school. The coefficients on *nonnucl* are negative on child labor and positive on schooling with statistically significance, which is similar to the result reported by Aggrawal [2004]. Given the same household size and the household asset, children belonging to the non-standard family type are better off. This can be attributed to more division of labor within an extended household, improving children's comparative advantage in learning. How this is achieved exactly is an issue left for further study focusing 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 guardians 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*. The contrast is sharper in the cl_2 and *enrol* regressions than in the cl_1 regression. 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 the guardians' 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 that coefficients on *hd_lit* and *sp_lit* are zero is not rejected. The χ^2 statistics reported in the table show this pattern in the cl_2 and *enrol* regressions but not in the cl_1 regression. Therefore, the test results are mixed, though in favor of the education of parents, not by the head's couple's.

These results give evidence (though weak) 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 is new and adds to the existing studies on the productivity of household enterprises in developing countries that the education level of the household head may not be the best indicator for household welfare (Yang [1997a], [1997b], Jolliffe [2002], Laszlo [2006]).

This 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 the child status directly, and 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 deciding the child status than the couple of the household head. However, as discussed already, since education also affects market and reservation wages of mothers and fathers, our results can also be compatible with the unitary approach.

The findings above raise a question what kind of these households are, 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 to the sample used in the previous subsection. Among them, 67 are from typical extended families where (1) the child's father is the eldest son of the household head and his spouse in the household, and (2) the child's mother is the wife of the son. Fifty children are from households where the child's father is absent and 40 children are from female headed households with the child's mother serving 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 are involved with 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).

IV.3 Robustness of the Regression Results

The findings above were robustly found from different specifications,[8] except for changes due to specifications already mentioned. First, the education level of the guardians of the child is measured by a continuous variable of schooling years, not by a literacy dummy. Second, the specifications using 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.

[8] These results are available on request.

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] (in this volume) 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.[9] In the literature, because of the overlapping of working and studying and also due to the existence of "idle" children[10] 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 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 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 regressions results first confirmed the previous, well-established results: parents' education is associated with less child labor and more school enrollment; richer households send their children less to work and more to school; and children in female-headed households are disadvantaged. Second, the results provide further evidence to the previous, non-established results: mothers' education matters more and equally important on boys and girls while fathers' education matters less and, if exists, significant on boys only; the impact of land is to reduce child labor and to increase schooling in the environment where the impact of land holding on improving marginal returns of child labor in farm work is small, possibly due to drought. Third, the results show 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/her spouse; households belonging to scheduled castes, scheduled tribes, and Muslim population tend to send their children to school, not to work, than households belonging to other backward castes.

[9] Namely, we used information collected in the one week time use module. The narrowly defined child work includes (1) remunerated work and (2) non-remunerated work. The broadly defined child work is the sum of (1), (2), (3) household chores, and (4) child care. Schooling time is as reported (see Sawada et al. [2006]).

[10] These children are also called "nowhere" children in the Indian context (see Lieten [2002] and

Although tentative, these findings have several policy implications. The last finding may suggest that that policy interventions targeted to 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. [2006]. This implies that targeting on mothers of current children, not on the household heads, is important in designing child labor eradication and school promotion policies. 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 versus collective household models is not attempted. See Sawada et al. [2006] and Fuwa et al. [2006] for such attempts using the same micro data.

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Table 1: Incidence of Child Labor in India among Children Aged 10-14

	All India						Rural Bihar-UP			Rural A.P.		
	NSS 1993/94			NSS 1999/2000			LSMS 1997/98			Survey 2005		
	National	Rural	Urban	National	Rural	Urban	Total	Boys	Girls	Total	Boys	Girls
"cl1" Market work (incl. hh ent)	9.3	10.8	4.8	6.6	7.5	3.7	11.4	12.2	10.5	43.3	39.0	48.1
"cl2 - cl1" Domestic work	8.4	9.6	4.7	5.9	6.6	3.6	16.9	3.2	34.0	6.7	2.8	11.1
Attend school	71.2	66.8	72.8	75.8	72.8	84.9	68.4	79.9	54.1	43.3	49.1	36.7

Sources: Edmonds et al. (2005) for NSS and Sakamoto (2006) for LSMS.

Table 2: Incidence of Child Labor in Rural Andhra Pradesh, 2005

	Aged 5-9			Aged 10-14		
	Total	Boys	Girls	Total	Boys	Girls
NOB	394	209	185	615	326	295
Percentage distribution of "Most important occupation"						
"cl1" Market work (incl. hh ent)						
Own farming (1)	1.53	0.51	2.55	10.21	8.65	11.86
Tenant farming (2)	0.51	0.51	0.51	0.49	0.64	0.34
Agricultural wage labor (3)	2.04	1.52	2.55	22.08	13.78	30.85
Livestock work (4)	4.58	3.55	5.61	9.23	14.10	4.07
Own household business (5 or 6)	0.25	0.00	0.51	1.15	1.92	0.34
Employee of other's business (7)	0.00	0.00	0.00	0.33	0.32	0.34
"cl2-cl1" Domestic work (12)	2.80	0.51	5.10	6.59	1.92	11.53
Student (13)	65.65	72.59	58.67	41.85	47.76	35.59
Idle & others						
Idle	18.58	19.80	17.35	3.79	5.13	2.37
Others	4.07	1.02	7.14	4.28	5.77	2.71
Currently enrolled in school	70.56	77.51	62.70	43.25	49.08	36.68

Table 3: Summary Statistics of Variables Used in the Logit Regression

Variable	NOB	Mean	Std.Dev	Min	Max
Dependent variables:					
cl1	1009	0.299	dummy	0	1
cl2	1009	0.353	dummy	0	1
enrl	1009	0.539	dummy	0	1
Explanatory variables:					
Individual characteristics of the child					
age	1009	10.185	2.694	5	14
age_squared	1009	34.137	26.908	0	81
sex	1009	0.470	dummy	0	1
Household or parental education					
lit_fat	1009	0.295	dummy	0	1
lit_mot	1009	0.099	dummy	0	1
hd_lit	1009	0.303	dummy	0	1
sp_lit	1009	0.093	dummy	0	1
Demographic characteristics					
hd_sex	1006	0.059	dummy	0	1
nonnucl	1009	0.244	dummy	0	1
no_fat	1009	0.105	dummy	0	1
no_mot	1009	0.140	dummy	0	1
hhsize	1006	7.787	3.710	3	29
infants	1006	0.549	0.904	0	5
children	1006	3.301	1.652	1	12
adeld	1006	3.533	1.908	1	12
Asset related information					
bplhold	1009	0.738	dummy	0	1
asset	1006	1.514	3.197	0	48.245
landval	1006	1.017	3.037	0	48
asset_ag	1006	0.034	0.114	0	1.7
asset_lv	1006	0.107	0.198	0	4.04
asset_hh	1006	0.356	0.486	0	7.02
Grandparents' information					
hdf_lit	979	0.249	dummy	0	1
spf_lit	1006	0.223	dummy	0	1
f_land	1009	6.056	10.463	0	80
m_land	1009	4.374	7.303	0	50
hdp_adiff	979	5.204	4.975	0	30
spp_adiff	992	4.580	4.538	0	25
Community dummies					
SC	1001	0.205	dummy	0	1
ST	1001	0.035	dummy	0	1
UMH	1001	0.039	dummy	0	1
Muslim	1001	0.036	dummy	0	1

Note: The number of observations is 1009 (those children reported in Table 2) except for several variables with missing information.

Table 4: Logit Regression Results (children belonging to the standard type households)

	cl1		cl2		enrl	
	Coef.	z	Coef.	z	Coef.	z
Model 1-1: Basic specifications						
age	0.770	3.11 ***	0.558	2.75 ***	0.236	1.70 *
age_squared	-0.016	-0.75	0.007	0.39	-0.064	-4.40 ***
sex	0.430	1.81 *	0.797	3.22 ***	-0.786	-3.58 ***
lit_fat	-0.660	-1.78 *	-0.751	-1.99 **	0.436	1.34
lit_fat*sex	0.445	0.90	1.231	2.56 ***	-0.705	-1.64 *
lit_mot	-2.217	-3.08 ***	-2.422	-3.71 ***	2.406	3.81 ***
lit_mot*sex	-0.002	0.00	0.591	0.69	0.092	0.11
hhsize	-0.001	-0.03	-0.018	-0.53	-0.006	-0.17
bplhold	0.255	0.92	0.030	0.11	0.393	1.54
asset	-0.049	-1.33	-0.057	-1.54	0.140	2.13 **
SC	-0.842	-3.12 ***	-0.621	-2.15 **	0.400	1.45
ST	-1.408	-1.30	-1.099	-1.05	1.328	1.64
UMH	-1.215	-1.43	-1.582	-2.05 **	1.714	2.63 ***
Muslim	-2.242	-2.82 ***	-1.448	-2.44 **	1.440	2.72 ***
Effective NOB		733		733		747
Wald chi2 for zero slopes		173.68 ***		204.13 ***		180.28 ***
Pseudo R2		0.3232		0.3438		0.2625
Model 1-2: Specifications distinguishing the source of household wealth						
age	0.764	3.11 ***	0.552	2.80 ***	0.233	1.67 *
age_squared	-0.014	-0.70	0.009	0.48	-0.064	-4.40 ***
sex	0.418	1.76 *	0.781	3.16 ***	-0.789	-3.59 ***
lit_fat	-0.639	-1.69 *	-0.776	-1.99 **	0.394	1.19
lit_fat*sex	0.470	0.94	1.241	2.55 **	-0.744	-1.71 *
lit_mot	-2.318	-3.17 ***	-2.590	-3.79 ***	2.475	3.81 ***
lit_mot*sex	0.116	0.11	0.812	0.94	0.021	0.03
hhsize	0.000	0.00	-0.025	-0.70	-0.010	-0.31
bplhold	0.214	0.76	-0.020	-0.08	0.397	1.57
landval	-0.041	-1.32	-0.079	-1.38	0.096	1.97 **
asset_ag	1.233	1.32	1.863	2.05 **	-0.896	-0.94
asset_lv	0.250	0.34	0.918	1.15	0.600	1.02
asset_hh	-0.375	-1.55	-0.289	-1.29	0.449	2.20 **
SC	-0.854	-3.14 ***	-0.610	-2.11 **	0.418	1.51
ST	-1.520	-1.34	-1.453	-1.29	1.147	1.39
UMH	-1.220	-1.40	-1.578	-2.00 **	1.758	2.67 ***
Muslim	-2.268	-2.92 ***	-1.478	-2.61 ***	1.476	2.80 ***
Effective NOB		733		733		747
Wald chi2 for zero slopes		173.97 ***		201.33 ***		182.85 ***
Pseudo R2		0.3262		0.3497		0.2662
chi2(3) test: H0=Model 1-1		3.28 n.s.		6.97 *		4.70 n.s.

Notes: (1) Statisticallysignificant at 1% (***), 5% (**), and 10% (*).
(2) The number of gross observations used is 763. Due to "perfect" prediction by several fixed effects, the effective NOB is sometimes smaller than 763.
(3) All models are estimated by equation-by-equation logit with village fixed effects (jointly significant at the 1% level).
(4) In chi2(k) tests, the null hypothesis is Model 1-1.

Table 4: Logit Regression Results (continued)

	cl1			cl2			enrl		
	Coef.	z		Coef.	z		Coef.	z	
Model 1-3: Specifications distinguishing the composition of household demography									
age	0.772	3.14	***	0.562	2.80	***	0.219	1.58	
age_squared	-0.015	-0.73		0.008	0.44		-0.064	-4.49	***
sex	0.416	1.72	*	0.766	3.06	***	-0.753	-3.36	***
lit_fat	-0.641	-1.71	*	-0.743	-1.95	*	0.401	1.23	
lit_fat*sex	0.460	0.92		1.273	2.62	***	-0.757	-1.77	*
lit_mot	-2.202	-3.05	***	-2.364	-3.64	***	2.326	3.69	***
lit_mot*sex	0.028	0.03		0.595	0.70		0.067	0.08	
infants	0.133	0.96		0.094	0.67		-0.267	-2.10	**
children	-0.008	-0.11		0.034	0.45		-0.054	-0.77	
adeld	-0.063	-0.84		-0.100	-1.36		0.163	2.25	**
bplhold	0.255	0.92		0.026	0.10		0.375	1.45	
asset	-0.048	-1.34		-0.054	-1.59		0.125	2.03	**
SC	-0.826	-3.02	***	-0.610	-2.09	**	0.355	1.25	
ST	-1.385	-1.27		-1.134	-1.08		1.325	1.57	
UMH	-1.241	-1.44		-1.622	-2.08	**	1.829	2.79	***
Muslim	-2.232	-2.74	***	-1.493	-2.42	**	1.524	2.69	***
Effective NOB		733			733			747	
Wald chi2 for zero slopes		175.08	***		204.71	***		190.7	***
Pseudo R2		0.3244			0.3454			0.2695	
chi2(2) test		1.12	n.s.		1.69	n.s.		7.35	**
Model 1-4: Specifications with additional variables characterizing non-coresident grandparents									
age	0.770	3.04	***	0.542	2.63	***	0.266	1.85	*
age_squared	-0.014	-0.68		0.010	0.53		-0.071	-4.62	***
sex	0.524	2.10	**	0.895	3.42	***	-0.981	-4.14	***
lit_fat	-0.478	-1.16		-0.548	-1.32		0.046	0.13	
lit_fat*sex	0.405	0.77		1.264	2.50	**	-0.706	-1.60	
lit_mot	-2.004	-2.53	**	-2.120	-3.11	***	2.750	3.67	***
lit_mot*sex	0.063	0.05		0.402	0.44		-0.296	-0.31	
hhsize	-0.012	-0.33		-0.037	-0.98		-0.002	-0.04	
bplhold	0.028	0.09		-0.061	-0.22		0.622	2.08	**
asset	-0.025	-0.45		-0.033	-0.77		0.147	2.02	**
hdf_lit	-0.396	-1.37		-0.079	-0.29		0.742	2.64	***
spf_lit	-0.577	-1.80	*	-0.897	-2.94	***	0.885	3.19	***
f_land	-0.029	-1.82	*	-0.022	-1.29		0.016	1.01	
m_land	0.022	1.36		0.008	0.48		-0.020	-1.17	
hdp_adiff	-0.023	-0.79		0.010	0.35		0.032	1.13	
spp_adiff	0.036	1.14		-0.028	-0.85		0.032	1.11	
SC	-0.818	-2.84	***	-0.833	-2.67	***	0.701	2.45	**
ST	-1.646	-1.43		-1.273	-1.18		1.640	1.80	*
UMH	-0.934	-0.94		-1.122	-1.25		1.503	2.00	**
Muslim	-2.456	-2.86	***	-1.672	-2.74	***	1.675	3.01	***
Effective NOB		697			697			707	
Wald chi2 for zero slopes		171.2	***		191.68	***		184.19	***
Pseudo R2		0.3325			0.3567			0.3061	
chi2(6) test		12.25	*		11.23	*		23.46	***

Table 5: Logit Regression Results (using all children in the sample)

	cl1			cl2			enrl		
	Coef.	z		Coef.	z		Coef.	z	
Model 2-1: Specifications using parents' education									
age	0.630	2.92	***	0.504	2.77	***	0.161	1.41	
age_squared	-0.010	-0.54		0.004	0.26		-0.050	-4.25	***
sex	0.536	2.70	***	0.831	4.09	***	-0.728	-4.04	***
lit_fat	-0.786	-2.41	*	-0.801	-2.51	**	0.475	1.76	*
lit_fat*sex	0.171	0.39		0.736	1.78	*	-0.247	-0.67	
lit_mot	-2.146	-3.12	***	-2.345	-3.77	***	2.029	3.64	***
lit_mot*sex	-0.007	-0.01		0.704	0.89		-0.052	-0.07	
hd_sex	0.766	1.54		0.807	1.56		-1.095	-2.54	**
nonnucl	-0.902	-2.44	**	-0.714	-1.95	*	0.922	2.97	***
no_fat	-0.114	-0.25		-0.335	-0.72		-0.179	-0.46	
no_mot	0.285	0.58		0.384	0.74		-0.932	-2.21	**
hhsize	-0.038	-1.36		-0.049	-1.65	*	-0.014	-0.52	
bplhold	0.162	0.70		0.023	0.10		0.322	1.57	
asset	-0.019	-0.67		-0.021	-0.79		0.076	2.01	**
SC	-0.779	-3.35	***	-0.634	-2.65	***	0.323	1.41	
ST	-1.307	-1.60		-0.017	-0.02		-0.088	-0.13	
UMH	-1.230	-1.90	*	-1.246	-2.23	**	1.602	3.27	***
Muslim	-2.063	-2.89	***	-1.316	-2.33	**	1.409	2.93	***
Effective NOB		1016			1016			994	
Wald chi2 for zero slopes		214.44	***		242.05	***		210.05	***
Pseudo R2		0.3033			0.3188			0.2366	
Model 2-2: Specifications using the education of the household head and his/her spouse									
age	0.660	2.98	***	0.529	2.90	***	0.122	1.06	
age_squared	-0.013	-0.68		0.001	0.09		-0.047	-4.00	***
sex	0.525	2.63	***	0.787	3.89	***	-0.712	-3.93	***
hd_lit	-0.868	-2.74	***	-1.062	-3.37	***	0.789	2.85	***
hd_lit*sex	0.219	0.51		1.072	2.61	***	-0.575	-1.56	
sp_lit	-2.446	-3.04	***	-1.378	-2.46	**	1.159	2.34	**
sp_litr*sex	0.286	0.26		-0.350	-0.47		0.871	1.32	
hd_sex	0.412	0.84		0.409	0.82		-0.772	-1.75	*
nonnucl	-0.763	-2.54	**	-0.644	-2.11	**	0.352	1.45	
no_fat	dropped			dropped			-3.350	-2.09	**
no_mot	0.192	0.45		0.205	0.48		-0.093	-0.26	
hhsize	-0.043	-1.56		-0.052	-1.80	*	0.008	0.33	
bplhold	0.131	0.56		0.012	0.05		0.371	1.80	*
asset	-0.010	-0.34		-0.015	-0.57		0.065	1.91	*
SC	-0.804	-3.41	***	-0.635	-2.64	***	0.392	1.71	*
ST	-1.238	-1.46		0.243	0.26		-0.314	-0.44	
UMH	-1.256	-1.93	*	-1.298	-2.36	**	1.649	3.49	***
Muslim	-2.062	-2.95	***	-1.301	-2.34	**	1.429	3.07	***
Effective NOB		1010			1010			994	
Wald chi2 for zero slopes		211.96	***		232.45	***		225.73	***
Pseudo R2		0.3039			0.3127			0.2319	

Notes: (1) Statisticallysignificant at 1% (***), 5% (**), and 10% (*).
(2) The number of gross observations used is 1016. Due to "perfect" prediction by several fixed effects, the effective NOB is sometimes smaller than 1016.

Table 5: Logit Regression Results (continued)

	cl1			cl2			enrl		
	Coef.	z		Coef.	z		Coef.	z	
Model 2-3: Specifications using both groups of education variables									
age	0.652	2.94	***	0.506	2.79	***	0.157	1.39	
age_squared	-0.012	-0.63		0.005	0.28		-0.050	-4.26	***
sex	0.585	3.30	***	0.791	3.87	***	-0.792	-5.12	***
lit_fat	-0.270	-0.65		-0.088	-0.17		-0.004	-0.01	
lit_fat*sex				-0.092	-0.11				
lit_mot	-1.037	-1.78	*	-1.853	-2.75	***	1.751	2.62	***
hd_lit	-0.500	-1.22		-0.902	-1.79	*	0.447	1.30	
hd_lit*sex				1.077	1.34				
sp_lit	-1.437	-2.27	**	-0.091	-0.13		0.300	0.47	
hd_sex	0.440	0.95		0.517	1.11		-0.580	-1.41	
nonnucl	-0.856	-2.53	**	-0.680	-1.97	**	0.763	2.64	***
no_fat	0.086	0.18		-0.226	-0.45		-0.517	-1.33	
no_mot	0.212	0.47		0.275	0.59		-0.374	-1.03	
hhsize	-0.040	-1.45		-0.050	-1.71	*	-0.004	-0.14	
bplhold	0.145	0.62		0.019	0.09		0.348	1.70	*
asset	-0.012	-0.42		-0.018	-0.66		0.069	1.93	*
SC	-0.812	-3.43	***	-0.627	-2.59	***	0.329	1.43	
ST	-1.248	-1.47		-0.076	-0.09		-0.200	-0.29	
UMH	-1.229	-1.87	*	-1.211	-2.14	**	1.588	3.23	***
Muslim	-2.060	-2.83	***	-1.291	-2.27	**	1.411	2.94	***
Effective NOB		1016			1016			994	
Wald chi2 for zero slopes		217.54	***		248.33	***		212.63	***
Pseudo R2		0.3076			0.3203			0.2347	
chi2(k): parents		4.17	n.s.		8.63	**		6.95	**
chi2(k): head and spouse		8.36	**		3.31	n.s.		2.07	n.s.

Note: "chi2(k): parents" tests all coefficients on parents' education = 0. "chi2(k): head and spouse" tests all coefficients on head and spouses' education = 0. k=2 for cl1 and enrl, k=3 for cl2.