Is There a Mothers' Dilemma?: Credit Constraint, Mothers' Work and Gender Disparity in Intrahousehold Time Allocation in Rural India

August, 2007

Nobuhiko Fuwa[♦]**, Seiro Ito**[♣]**, Kensuke Kubo**[♥]**, Takashi Kurosaki**[*]**, and Yasuyuki Sawada**[♠]

Abstract

This paper examines the relationships among credit constraint, mothers' labor supply and children's time allocation in rural Andhra Pradesh, India, where a high prevalence of child labor poses serious problems. We estimate determinants of time allocation among children and of the gender gap between girls and boys in various activities treating both credit constraint and mothers' labor supply as endogenous variables. As expected, boys spend longer time in school than do girls, while girls spend longer time on household chores than do boys. When mothers increase their labor supply, however, the gender gap in children's time allocation (esp. schooling) does not appear to be affected significantly. We also find that a binding credit constraint significantly reduces children's schooling and leisure time and increases their domestic work time, but that the gender gap in children's time allocation (esp. schooling) appears to be smaller in credit-constrained households than in unconstrained households.

Keywords: child labor, schooling, gender bias, credit constraint, household models.

[♦] Graduate School of Science and Technology, Chiba University. E-mail: nfuwa@faculty.chiba-u.jp
[♣] Development Studies Center, Institute of Developing Economies. E-mail: itohse@ide.go.jp.
[♥] Development Studies Center, Institute of Developing Economies. E-mail: kuboken@ide.go.jp.
[*] The Institute of Economic Research, Hitotsubashi University. E-mail: kurosaki@ier.hit-u.ac.jp.
[♠] Faculty of Economics, University of Tokyo. E-mail: sawada@e.u-tokyo.ac.jp.

1. Introduction

This paper focuses on a typical dilemma faced by mothers in poor, credit constrained households in rural India. On the one hand, particularly for poor and credit constrained households, marginal utility of income/consumption that could be obtained through increasing mothers' labor supply is likely to be very high.[1] In addition, and more importantly, the recent empirical literature on intrahousehold resource allocation has shown that a greater share of the income brought into the household by women (including mothers) can have beneficial effects on the current and future welfare of children. According to the 'collective-model' interpretation of household resource allocation behavior, an increase in the share of income brought into the household by women would enhance her 'bargaining power' and the allocation of consumption and investments will likely be geared toward reflecting more of women's preferences, such as health and nutrition of children (e.g., Thomas 1990; Lundberg et al 1994, see Behrman (1997) for a critical survey). Thomas (1990) further finds some evidence that the marginal positive effects on nutrition of mothers' incomes are higher on girls' than on boys' (and higher than father's marginal impact on boys').

On the other hand, however, increasing mothers' remunerative work could require her to reduce her time spent on household production (i.e., child care and other household chores such as fetching water, cooking and cleaning), which is likely to be taken over, at least partially, by their children. This would place strong strain on children's time allocation. The increasing strain on children's time allocation induced by the increase in mothers' labor supply has an additional gender dimension in intrahousehold resource allocation, viz. the gender disparity in schooling between girls and boys. Girls could be particularly disadvantaged in poor and resource constrained households since siblings/children in such households need to compete for scarce resources and boys tend to be in more favorable positions because investments in boys yield higher future returns to parents than do investments in girls (e.g., Mammen and Paxon 2000; Garg and Morduch 1998).

Those observations suggest that credit constraint, female labor supply and intrahousehold time allocation are tightly intertwined, and such interactions are the focus of this paper. Such recognition is by no means new, and the potential trade-offs between mothers' labor supply and children's schooling has been well recognized within the development community (e.g., Ilahi 2000). However, rigorous analyses disentangling the relationships among those aspects have been hampered by the fact that all of them are endogenous variables. While a common approach for addressing endogeneity is instrumental variables estimation, it is typically difficult to find credible instrumental variables for all the endogenous variables, especially in the context of cress-section data. There has been some indirect evidence in the literature, however, on potential trade-offs. Skoufias (1993), for example, finds a significantly negative relationship between (adult) female wages and time allocation of children on schooling. Nevertheless, to our knowledge, there has not been a study directly focusing on the relationship among mothers' labor supply, children's time allocation and credit access with explicit control for endogeneity.

In our attempts to identify the effects of mothers' labor supply and credit access on children's time allocation by controlling for the endogeneity problem of both variables, we utilize somewhat different identifying assumptions for the two variables; while we rely on a usual exclusion restriction (or 'zero-restriction') for identifying the effects of credit constraint, we utilize a weaker

[1] Such a possibility is consistent with the initial (downward) phases of the so called U-hypothesis of female labor supply in the process of economic development, as observed by Goldin (1995) and Mammen and Paxson (2000); according to this hypothesis, female labor force participation tends to decline in early stages of economic development (when women mainly work on family farms and household enterprises) and then to increase in later stages (when wage employment in modern sector becomes dominant). Empirical regularities supporting the hypothesis have been found, for example, in India and Thailand (Mammen and Paxson 2000).

(‘non-zero restriction’) assumption for identifying the effects of mothers’ labor supply by focusing on its effects on the gender gap in (rather than the levels of) children’s time allocation. Our identification strategy can be seen as a combination of Japelli (1990)’s approach of treating credit constraint as endogenous and Pitt and Rosenzweig (1990)’s approach of identification in intrahousehold time allocation contexts.

This study utilizes a special household survey collected in rural Andrah Pradesh in India, where incidence of child labor is found to be relatively high. This dataset contains two special data ‘modules’ that are typically not available in large scale household surveys; time use data and credit access data. The detailed time-use module records time allocation of all household members in various aspects, allowing us to make the critical distinctions among time spent on schooling, remunerative work, household chores including child care and leisure, unlike most of the typical household survey data where the latter three activities can not be distinguished. In addition, the credit module collects detailed information about access to credit which, in turn, allows us to distinguish credit constrained and unconstrained households and to model the determination of credit market access explicitly.

The remainder of this paper is organized as follows. Section 2 presents a theoretical framework, from which we derive empirical specifications adopted in this paper and which underlie our interpretation of the empirical results. Section 3 discusses our empirical specification and the identification strategy. Section 4 describes the data used in our econometric estimation, characterizing children’s activities and credit access observed in our dataset. Section 5 presents our main empirical results. Section 6 concludes the paper with some policy implications based on our empirical findings.

2. A Theoretical Framework

As the conceptual framework underlying our empirical specifications, we first develop a two-period model of a household consisting of a child, his/her father, and his/her mother. The household’s objective is to maximize a household utility function[3]:

$$U(C_1, F_1, M_1, L_1) + U(C_2, F_2, M_2, L_2)/(1+\delta) \qquad (1)$$

with respect to C_1, F_1, M_1, L_1, and S, subject to the constraints (2)-(5) specified below, where δ is the subjective discount rate, C_t is the household’s consumption, F_t the father’s labor supply, M_t the mother’s labor supply, L_t the child’s labor supply (t=1, 2), and S the net saving in period 1. The first period budget constraint is given by

$$C_1 + S = Y_1 + w_F F_1 + w_M M_1 + w_C L_1, \qquad (2)$$

And the second period budget constraint is

$$C_2 = Y_2 + (1+r)S + w_F F_2 + w_M M_2 + f(T-L_1)L_2, \qquad (3)$$

where r is the market interest rate, Y_t is unearned income, w_k is wage, $f(.)$ is a function determining gross returns to human capital investment in the child ($f'>0$, $f''<0$), and T is the time endowment.

[2] 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.

[3] We assume that the household is a collective unit that behaves as a single economic agent (i.e., the unitary household assumption) and assume away the potentials of intra-household bargaining. An extension of this model under a ‘non-unitary’ model assumption is discussed in Fuwa et al (2006). In our empirical analysis, however, we will include potential shifters of the aggregate household preferences that can be interpreted as ‘extra environmental parameters (EEP)’ *a la* McElroy (1990).

Household decisions are also subject to time and credit constraints

$$0 \leqq F_t, M_t, L_t \leqq T, \quad t=1,2 \tag{4}$$
$$S \geqq -K, \tag{5}$$

where K is the exogeneous borrowing limit imposed on the household. For simplicity, labor supply in the second period is assumed to be fixed and we focus on the 1st period decision making.

Inserting (2) and (3) into (1), letting λ denote the Lagrange multiplier on (5), and assuming an interior solution for (4), the first order conditions necessary for the optimality include

$$S: \quad -U_{C1} + U_{C2}(1+r)/(1+\delta) + \lambda = 0, \tag{6}$$
$$F_1: \quad U_{F1} + w_F U_{C1} = 0, \tag{7}$$
$$M_1: \quad U_{M1} + w_M U_{C1} = 0, \tag{8}$$
$$L_1: \quad U_{L1} + w_C U_{C1} - f'(.)L_2 U_{C2}/(1+\delta) = 0, \tag{9}$$
$$\lambda: \quad \lambda(S+K) = 0, \tag{10}$$

where subscripts on U show partial derivatives. There are two possible cases under this framework depending on the credit constraint (5) is binding.

<u>The case with non-binding credit constraint</u>
Since $\lambda = 0$, equation (6) becomes

$$U_{C1} = U_{C2}(1+r)/(1+\delta), \tag{6'}$$

which is the standard Euler equation, where marginal rate of substitutions are equalized to the interest rate. Equation (9) becomes

$$U_{L1} + \{w_C \quad - f'(.)L_2/(1+r)\}U_{C1} = 0, \tag{9'}$$

which shows that $\{w_C - f'(.)L_2/(1+r)\}$ is the shadow wage of child labor in period 1. When the child works in period 1, the household obtains wage income at the rate of w_C but the child labor reduces human capital investment and thereby reduces the wage rate in period 2. The household allocates child labor in period 1 considering this effect. Since equation (10) is automatically satisfied when $\lambda = 0$, we can solve four equations (6'), (7), (8), and (9') for four endogenous variables S, F_1, M_1, and L_1.

<u>The case with binding credit constraint</u>
Since $\lambda > 0$, equation (6) becomes

$$U_{C1} = U_{C2}(1+r)/(1+\delta) +\lambda > U_{C2}(1+r)/(1+\delta). \tag{6''}$$

Since the marginal utility of consumption in period 1 is higher than that in period 2, the household would prefer to increase the first period consumption but it cannot, because the credit constraint is already binding ($S = -K$). Equation (9) becomes

$$U_{L1} + \{w_C - (1 - \mu) f'(.)L_2/(1+\mathrm{r})\}U_{C1} = 0, \tag{9''}$$

where $\mu = \lambda/U_{C1}$, $0<\mu<1$. Equation (9'') shows that the difference of the shadow wage from the child's nominal wage is reduced. In other words, because of the binding credit constraint, the subjective interest rate goes up and the optimal human capital investment therefore decreases (the optimal child labor in period 1 increases).

By solving the system of five equations comprising (6"), (7), (8), (9), and the relation $S+K=0$ ((10") from equation (10)), we obtain the optimal solution for five endogenous variables S, F_1, M_1, L_1, and λ. The system can be divided into (10") which includes only S, a sub-system of equations (7)-(9) which does not include λ, and (6") which includes F_1, M_1, L_1, and λ. Therefore, the system can be solved in a sequential way: first, determine S from (10"); second, solve the subsystem (7)-(9) to obtain F_1, M_1, L_1; third, insert these four into (6") to obtain λ. This sequential solution is utilized in below to derive an endogenous switching model for the credit constraint.

The Gender Gap in Children's Education

Given the total resources devoted to children's education in the first period (T-L_1), which could vary, in particular, depending on the household access to credit market, our next concern is how such resources are allocated between girls and boys. As a conceptual framework that will aid the interpretation of our empirical results on the gender gap in schooling in a later section, we adopt the intrahousehold resource allocation model first proposed by Behrman, Pollack and Taubman (1982). The model demonstrates that the gender gap in schooling (or distribution of any household resource, such as nutrients, health care, etc.) is determined as the interactions between the shape of parental preferences and that of the production possibility frontier arising from human capital investment. In the rest of this section, in order to focus on the gender gap in schooling between girls and boys, we follow Behrman et al (1982) and assume that parents are altruistic in the sense that they care the wealth of children and that the parental (household) utility function is separable between the children's wealth and the other elements of household utility (consumption and leisure) as expressed in equation (1). The parental utility function defined over their children's lifetime earnings/wealth takes the form::

$$W(Y_g, Y_b), \tag{11}$$

where Y_g and Y_b are wealth (lifetime incomes) of girls and boys, respectively, as they are adults. There are two constraints: (1) the total resources devoted to children's education, as determined in the previous subsection, and (2) the production function of investing in human capital:

$$Y_i = f(E_i; G_i) \text{ for i = girls, boys,} \tag{12}$$

where E_g ($=T$-L_{g1}) and E_b ($=T$-L_{b1}) are, respectively, girls' and boys' schooling, and G_g and G_b are 'endowment' of girls and boys, respectively. We assume that $f_E(.) > 0$ and $f_{EE}(.) < 0$. Here the 'endowments' include all determinants of children's earnings predetermined prior to schooling, including genetically inherited traits such as innate ability, physical strength, etc. To the extent that gender disparities arise in labor market outcomes, a child's sex is also considered as an endowment for the purpose of this model (Behrman 1997, 130). As shown in detail in Berhrman (1997), how the differential human capital investments among children (among siblings) may respond to resource/credit constraint in this model can be analyzed using simple diagrams. The combination of the two constraints, the total parental resources (including the forgone income from child labor) devoted to children's education and the educational production function, forms production possibility frontiers (PPFs). The diminishing marginal returns from schooling ensures convex PPFs, as shown in Figure 1 and Figure 2, where boys' adult earnings (Y_b) are measured along horizontal axis and girls' adult earnings (Y_g) along vertical axis. In both Figure1 and 2, we drew the same set of two PPFs; PPF1 corresponding to unconstrained households and PPF2 corresponding to resource constrained (or credit constrained) households; as the total household wealth increase, and thus the total resources that parents can devote to education increase the PPF shifts further away from the origin.

In this theoretical framework, the differential effects along gender of differential amounts of total resources devoted to children's schooling (i.e., differential PPFs) can be analyzed in an analogous manner as Behrman et al (1989)'s analysis of inequality in college education among siblings. Following Behrman et al (1989), we assume that the parental preferences take the form of a translated CES:

$$W(Y_g, Y_b) = \left[a_g (Y_g - Y_g^n)^c + a_b (Y_b - Y_b^n)^c\right]^{1/c}, \qquad (13)$$

where parameters Y_g^n and Y_b^n are the minimum (e.g., subsistence) level of earnings for girls and boys, respectively, above which parents are willing to trade off the earnings of girls against boys, a_g and a_b are relative weights that parents place on girls versus boys, respectively, and c reflects the degree of 'inequality aversion' of the parents. In one extreme (where c=1) of parental behavior toward inequality is 'zero inequality aversion'; parents do not care the relative distribution of earnings between girls and boys and parental utility depends only on the sum of all the children's earnings. In this case, the parents' indifference curves become straight lines with slope -1. The opposite extreme, on the other hand, is when c = -∞, where parents exhibit 'infinite inequality aversion' (or the Rawlsian behavior) of valuing additional earnings only if they are received by the worst-off child (e.g., Behrman et al, 1989, 402). In this case, the parents' indifference curves become L-shaped. Figure 1 illustrates a case of parental preferences with very weak inequality aversion (parameter c is close to 1) and Figure 2 illustrates a case with very strong inequality aversion (parameter c close to -∞). Furthermore, the indifference curves in both Figure 1 and 2 are drawn with an additional assumption of 'equal concern' between girls and boys so that all the indifference curves are symmetric around the 45^o ray. This is equivalent to assuming $a_g = a_b$ in the parental welfare function above.[4]

In both Figure 1 and 2, PPFs are drawn so that PPF2 for resource constrained households is relatively more symmetric (around the 45^o ray) while PPF1 for resource unconstrained households is elongated along the horizontal axis, reflecting an additional assumption that boys' marginal returns from schooling is higher than those of girls for the same level of education and thus the optimal level of education (where the returns to education equals market interest rate) is higher for boys than for girls; i.e., boys are more 'educable' than are girls, according to Behrman (1997)'s expression. Assuming (further) that the minimum/subsistence level of human capital for girls and boys are similar ($Y_g^n \approx Y_b^n$), PPFs become more symmetric as they are closer to the origin, as shown in Figures 1 and 2, that is, as the total household resources devoted to children become smaller. As a result, as shown in Figure 1, *if parental inequality aversion is relatively weak,* then the gender disparity in schooling is likely to become smaller as the total resources devoted to children become smaller; Behrman et al (1989) call this phenomenon "preference displacement effect" (p. 403). This implies that the gender disparity in schooling may be smaller among credit constrained households than in unconstrained households, given all the theoretical assumptions stated above hold. This can be seen in the comparison between the tangency points A and B in Figure 1. In contrast, however, Figure 2 shows that *if parental inequality aversion is sufficiently strong*, then the gender disparity in schooling may not increase as the total resources devoted to child education increase, as can be seen in the comparison between the tangency points A and B in Figure 2. In the limiting case, where parental indifference curves take L-shape, parents would ensure equal earnings between girls and boys regardless of the relative marginal returns to education between girls and boys (i.e., regardless of the shape of PFFs). In our empirical analysis later, we will examine the gender disparity in schooling between credit constrained and unconstrained households, which would give us some indications of parental preferences in terms of inequality aversion.

---

[4] Behrman (1988) empirically estimated the parameters of parental welfare function using the ICRISAT data from India. He finds that while parents exhibit 'unequal concern' favorable to boys (about 5% biased toward boys) during the lean season (when households are more resource constrained), 'equal concern' cannot be rejected during the surplus season. He similarly finds that parental inequality aversion is relatively strong (and substantially stronger than the measured inequality aversion observed in the United States by Berhman et al, 1982) during the surplus season while it is much weaker (and weaker than in the US) during the lean season.

3. Empirical Specifications and the Identification Strategy

In this study, our focus is on the interactions among mothers' labor supply (M), children's time allocation (L) and the credit constraint (λ). In particular, we are interested in whether an increase in mothers' labor supply could widen the gender gap in schooling and work among children, and, furthermore, whether such potential trade-offs are aggravated by credit constraint. Since all of the three variables are endogenous in our model, additional assumptions are required to empirically identify the relationships that we are interested in.

Reduced form time allocation

Our empirical investigation proceeds in a sequential manner. We start with a set of reduced form equations determining time allocation of children, which can be derived from the theoretical model discussed above. Given our focus on the gender gap, we estimate reduced form time allocation models for girls and boys separately, as follows (in the followings, time subscripts are dropped and subscript *h* for a household, subscript *i* for a child type, girl or boy, and subscript *j* for activity type (schooling, remunerative work, household chore, or leisure) are used):

$$L_{hij} = \boldsymbol{\alpha}_0 + \boldsymbol{X}_{hi}'\boldsymbol{\alpha}_{1ij} + \boldsymbol{X}_h'\boldsymbol{\alpha}_{2ij} + \mathrm{u}_{\mathrm{ij}} \qquad (14)$$

where X is the shifter of market returns of child labor and schooling, the interest rate and credit constraints faced by the household, and the preferences of the household, including: child's age and sex in X_i; household head's characteristics, household's demographic characteristics, and household assets in X_h, and u_{hi} is a mean zero error term. To control for differences in local market conditions and preferences, we also include village fixed effects and community fixed effects. As the dependent variables for (14), we include not only the time used in schooling and remunerative works but also the time used in child care and domestic chores since these are also important work activities. We also examine the determinants of leisure time.

Moving toward the Conditional Demand Function Approach: credit constraint and children's time allocation

We next examine how credit access affects time allocation among children. This can be done as an application of the 'conditional demand function approach.'[6]

$$L_{hij} = \alpha_{0ij} + \boldsymbol{X}_{hi}'\boldsymbol{\alpha}_{1ij} + \boldsymbol{X}_h'\boldsymbol{\alpha}_{2ij} + \alpha_{ccj}cc_h + u_{ij} \qquad (15)$$

where cc_{h} is an endogenous dummy variable (defined at the household-level) indicating whether the household is credit constrained (cc=1) or not (cc=0).[7] Assuming that the effects of all the covariates $\boldsymbol{X}_{hi}$ and $\boldsymbol{X}_h$ are the same between credit constrained and unconstrained households, coefficient α_{ccij} measures the effects of the lack of access to credit on the time spent on various activities (j) by children in the age and gender group i. Household access to credit, in turn, is determined by :

[5] Wage rates of the father and the mother may also shift ω. However, since wage rates also changes comparative advantages of market work and leisure within a household, they should also affect the marginal rate of substitution between consumption and leisure directly. Therefore, exclusion tests for wage rates cannot be used to test unitary against non-unitary household models (Alderman et al. 1995; Doss 1996).

[6] The discussion of the approach dates back at least to Pollak (1969), and a thorough discussion of the use of this approach in the context of intrahousehold resource allocation issues can be found in Pitt (1997).

[7] We will discuss how to determine which households are credit constrained in the next section.

$cc_h = 1$ if $\lambda_h^* \geqq 0$ and $cc_h = 0$ if $\lambda_h^* \leqq 0$, (16)

$\lambda_h^* = \boldsymbol{X}_h'\boldsymbol{\beta}_1 + \beta_2 K_h + e_h$, (17)

where λ_h^* is the (unobserved) Lagrange multiplier associated with the credit constraint, as defined in the previous section. K_h, as introduced in the theoretical model, is the exogenous shifter of the amount of credit that household *h* has access to. The observed measure of K_h we will use in our empirical implementation is the value of land that household *h* holds. Our identifying assumption (exclusion restriction) follows Sawada et al (2006), which states that the value of land that each household holds affects credit access (e.g., through its collateral values) but it does not directly affect time allocation patterns of household members (instead, as we will see later, we include the physical size of *irrigated* land as a determinant of time allocation). Assuming joint normality, coefficients of the models specified with (15) (16) and (17) can be estimated as an application of "Type 5 Tobit" model discussed in Amemiya (1985).

Conditional Demand Function with Endogenous Regime Switching: credit constraint, mothers' labor supply and the gender gap in children's time allocation

Building on the models above, we now proceed to address our main questions of whether an increase in mothers' labor supply worsens the gender gap in schooling and work among children, and, furthermore, whether such potential trade-offs are aggravated by credit constraint. Instead of restricting the effect of credit access on children's time allocation to the intercept effects (α_{ccj}) alone, we could alternatively allow the effects of covariates $\boldsymbol{X}_{hi}$ and $\boldsymbol{X}_h$ (as well as the intercept) on children's time allocation to differ between credit constrained and unconstrained households, as follows:

$L_{hijc} = \alpha_{0ijc} + \boldsymbol{X}_{hi}'\boldsymbol{\alpha}_{1ijc} + \boldsymbol{X}_h'\boldsymbol{\alpha}_{2ijc} + u_{hijc}$, if $cc_h = 1$, (18a)

$L_{hiju} = \alpha_{0iju} + \boldsymbol{X}_{hi}'\boldsymbol{\alpha}_{1iju} + \boldsymbol{X}_h'\boldsymbol{\alpha}_{2iju} + u_{hiju}$, if $cc_h = 0$, (18b)

with the determination of endogenous 'regime' switching between the 'credit constrained' and the 'unconstrained' status being given by (16) and (17). In equations (18a) and (18b), subscript c corresponds to the cases where households are credit constrained and subscript u to the cases where households are unconstrained.[8] With these modified reduced form equations for children's time use (18a) and (18b), we introduce an additional (endogenous) right hand side variable, M_h:

$L_{hijc} = \delta_{ijc}M_h + \alpha_{0ijc} + \boldsymbol{X}_{hi}'\boldsymbol{\alpha}_{1ijc} + \boldsymbol{X}_h'\boldsymbol{\alpha}_{2ijc} + \phi_{hc} + u_{hijc}$, if $cc_h = 1$, (19a)

$L_{hiju} = \delta_{iju}M_h + \alpha_{0iju} + \boldsymbol{X}_{hi}'\boldsymbol{\alpha}_{1iju} + \boldsymbol{X}_h'\boldsymbol{\alpha}_{2iju} + \phi_{hu} + u_{hiju}$, if $cc_h = 0$, (19b)

where M_h is mother's labor supply and we also have added unobserved fixed effects that affect time allocation of household members (ϕ_{hc} and ϕ_{hu}). We further assume that the (endogenous) mothers' labor supply is determined by:

$M_h = \beta_0 + \boldsymbol{X}_{hi|i=mother}'\boldsymbol{\alpha}_1 + \boldsymbol{X}_h'\boldsymbol{\beta}_{1h} + u_{hm}$, (19)

which can be derived in the exact same manner as the reduced form time allocation equation for

[8] If all the coefficients in the vectors $\boldsymbol{\alpha}_{1ij}$ and $\boldsymbol{\alpha}_{2ij}$, except for the intercept (α_{0c}), are the same between credit constrained and unconstrained households, then the model reduces to model (15) above.

children, equation (14), above by setting the household member index i as the mother, the activity index j as remunerative work. The individual-level covariate vector $\boldsymbol{X}_{hi}$ in equation (19) becomes the individual characteristics of the mother ($\boldsymbol{X}_{hi|i=mother}$).

A major challenge now is to devise an additional assumption that would allow us to identify coefficients δ_{ijc} and δ_{iju}. Arguably, typical exclusion restrictions may be difficult to justify in this context. While we need a variable that affects mothers' labor supply but not children's time allocation, such a variable is difficult to find. Any variable that affects one member(i.e., mother)'s time allocation is likely to affect other members(e.g., children)' time allocation as well.[9] Consequently, instead of searching for an additional exclusion restriction, we follow the approach taken by Pitt and Rosenzweig (1990) and use a somewhat weaker (i.e., more plausible) assumption. The endogeneity issue of mother's labor supply in equations (19a) and (19b) above can be addressed with a weaker assumption than an exclusion restriction by focusing on the *gender gap* in time allocation instead of the *level* of time use of girls and boys. Rather than assuming that some variables affect mothers' time allocation but not children's time allocation, we assume that some variables affect girls' and boys' time allocation in the identical manner. For example, the size of irrigated land would affect mothers' labor supply through its effects on on-farm labor of various household members. While it is also likely to have effects on children's time allocation, the effects may be similar between girls and boys. In fact, we will assume in our empirical implementation that most of the household-level characteristics — including household size, parents' education, household asset holding and caste dummies— operate in this manner, except for the number of 'infant' in the household. Since there is a distinct pattern in who are more likely to take care of small children, as we will see, the effects of the number of infants on time use are likely to be different by gender and by age group. With such an additional assumption (19a) can be rewritten as:

$$L_{hijc} = \delta_{ijc}M_h + \alpha_{0ic} + \boldsymbol{X}_{hi}'\boldsymbol{\alpha}_{1ijc} + \boldsymbol{X}_{hA}'\boldsymbol{\alpha}_{2Aijc} + \boldsymbol{X}_{hB}'\boldsymbol{\alpha}_{2Bjc} + \phi_{hc} + u_{hijc}, \qquad \text{if } cc_h = 1, \quad (19a')$$

where the vector of exogenous (household-level) variable $\boldsymbol{X}_h$ is now decomposed into the variables that have differential effects on girls and boys ($\boldsymbol{X}_{hA}$) and those that have identical effects on girls and boys($\boldsymbol{X}_{hB}$), with subscript *i* dropped from coefficient vector $\boldsymbol{\alpha}_{2Bjc}$. Furthermore, by focusing on the gender gap between girls' and boys' time allocation, instead of the level of time use, we take the difference between the time spent on activity j by girls (i = girls) and by boys (i = boys) using (19a'):

$$L_{higc} - L_{hibc} = (\delta_{gjc} - \delta_{bjc})M_h + (\alpha_{0gjc} - \alpha_{0bjc}) + (\boldsymbol{X}_{hi} - \boldsymbol{X}_{hi})'\boldsymbol{\alpha}_{1jc} + \boldsymbol{X}_{hA}'(\boldsymbol{\alpha}_{2Agjc} - \boldsymbol{\alpha}_{2Abjc}) + (u_{hgjc} - u_{hbjc}), \qquad \text{if } cc_h = 1, \quad (21a)$$

and similarly for unconstrained households (19b):

$$L_{higu} - L_{hibu} = (\delta_{gju} - \delta_{bju})M_h + (\alpha_{0gju} - \alpha_{0bju}) + (\boldsymbol{X}_{hi} - \boldsymbol{X}_{hi})'\boldsymbol{\alpha}_{1ju} + \boldsymbol{X}_{hA}'(\boldsymbol{\alpha}_{2Agju} - \boldsymbol{\alpha}_{2Abju}) + (u_{hgju} - u_{hbju}), \qquad \text{if } cc_h = 0, \quad (21b)$$

where a household member i =g stands for a girl and i=b for a boy, and we have additionally assumed that the effects of individual-level covariates ($\boldsymbol{\alpha}_{1jc}$ and $\boldsymbol{\alpha}_{1ju}$) are the same for girls and boys. Now the vector of household-level exogenous variables ($\boldsymbol{X}_{hB}$) can be used as identifying instrumental variables for controlling for endogeneity of mothers' labor supply (M_h) and idnetifying ($\delta_{gjc} - \delta_{bjc}$) and ($\delta_{gju} - \delta_{bju}$). The assumption here is that $\boldsymbol{X}_{hB}$ affects mother's labor supply but does not directly affect the *difference (i.e., gender gap)* in their children's time allocation on activity j. An additional advantage of focusing

[9] Conceptually, individual-level wage rates could potentially be such a candidate (see. E.g., Pitt 1997). Practically, however, often there is not sufficient variation in such variables, at least in cross-section data.

on the gender gap rather than the level is that unobserved household effects (ϕ_{hc}) are also eliminated by taking the difference.

One way to estimate the endogenous switching regression equation system (20), (21a) (21b) (16) and (17) is a two-step procedure with additional Mill's ratio terms as correction terms for endogenous regime switching (e.g., Maddala 1983). Assuming joint normality of error terms[10], we can rewrite the four error terms appearing in equations (21a) and (21b) as follows:

$$u_{hbjc} = -\sigma_{bc\varepsilon}\frac{\phi(\beta_1 X_{1h} + \beta_2 K_h)}{\Phi(\beta_1 X_{1h} + \beta_2 K_h)} + \varepsilon_{hbjc} \text{, where } E(\varepsilon_{hbjc} | X, M, K, cc_h = 1) = 0,$$

$$u_{hgjc} = -\sigma_{gc\varepsilon}\frac{\phi(\beta_1 X_{1h} + \beta_2 K_h)}{\Phi(\beta_1 X_{1h} + \beta_2 K_h)} + \varepsilon_{hgjc} \text{, where } E(\varepsilon_{hgjc} | X, M, K, cc_h = 1) = 0,$$

$$u_{hbju} = \sigma_{bu\varepsilon}\frac{\phi(\beta_1 X_{1h} + \beta_2 K_h)}{1-\Phi(\beta_1 X_{1h} + \beta_2 K_h)} + \varepsilon_{hbju} \text{, where } E(\varepsilon_{hbju} | X, M, K, cc_h = 0) = 0, \text{ and}$$

$$u_{hgju} = \sigma_{gu\varepsilon}\frac{\phi(\beta_1 X_{1h} + \beta_2 K_h)}{1-\Phi(\beta_1 X_{1h} + \beta_2 K_h)} + \varepsilon_{hgju} \text{, where } E(\varepsilon_{hgju} | X, M, K, cc_h = 0) = 0.$$

In these error terms, $\phi(\bullet)$ and $\Phi(\bullet)$ represent the standard normal density function and distribution function, respectively. The indicator variable, cc_h, indicating whether a household is credit constrained, is defined as in (16) and (17) above. Substituting those into (21a) and (21b) yields:

$$L_{higc} - L_{hibc} = (\delta_{gjc} - \delta_{bjc})M_h + (\alpha_{0gjc} - \alpha_{0bjc}) + (\boldsymbol{X}_{hi} - \boldsymbol{X}_{hi})'\boldsymbol{\alpha}_{1jc} + \boldsymbol{X}_{hA}'(\boldsymbol{\alpha}_{2Agjc} - \boldsymbol{\alpha}_{2Abjc}) - (\sigma_{gc\varepsilon} - \sigma_{bc\varepsilon})\frac{\phi(\beta_1 X_{1h} + \beta_2 K_h)}{\Phi(\beta_1 X_{1h} + \beta_2 K_h)} + (\varepsilon_{hgjc} - \varepsilon_{hbjc}), \text{ if } cc_h = 1 \quad (21a')$$

and

$$L_{higu} - L_{hibu} = (\delta_{gju} - \delta_{bju})M_h + (\alpha_{0gju} - \alpha_{0bju}) + (\boldsymbol{X}_{hi} - \boldsymbol{X}_{hi})'\boldsymbol{\alpha}_{1ju} + \boldsymbol{X}_{hA}'(\boldsymbol{\alpha}_{2Agju} - \boldsymbol{\alpha}_{2Abju}) + (\sigma_{gu\varepsilon} - \sigma_{bu\varepsilon})\frac{\phi(\beta_1 X_{1h} + \beta_2 K_h)}{1-\Phi(\beta_1 X_{1h} + \beta_2 K_h)} + (\varepsilon_{hgju} - \varepsilon_{hbju}), \text{ if } cc_h = 0 \quad (21b')$$

where $E(\varepsilon_{hgjc} - \varepsilon_{hbjc} | X, M, cc_h = 1) = E(\varepsilon_{hgju} - \varepsilon_{hbju} | X, M, K, cc_h = 0) = 0$.

Equations (21a') and (21b'), together with the determination of mothers' labor supply equation (20), can be estimated by separate two-stage least squares estimation: equation (21a') is estimated using only the sample households with binding credit constraint while Equation (21b') is estimated using only the sample households with unconstrained credit access. The inverse Mill's ratio terms can be obtained from the probit credit access equations, (16) and (17), as introduced earlier.

In sum, a major advantage of focusing on the gender gap in (rather than the level of) time use is that it allows us to control for the endogeneity problem of mothers' labor supply (with respect to children's time use) by using instrumental variables with a weaker assumption than a typical exclusion restriction. Additionally, by taking differences, the approach also allows us to control for the effects of unobserved household-level fixed effects. The cost of obtaining those benefits, however, is that with this approach we can identify the effects of mothers' labor supply only on the gender gap but not on the level of time spent by girls or by boys.

[10] We can elaborate an empirical framework without the assumption of multinormal distribution (Lee 1982). For example, Newey et al. (1990) proposed a procedure of nonparametric approximations for the sample selection correction terms. Yet, in general, these extensions provide comparable results to those derived under the joint normality assumption.

4. Data

4.1. The Household Survey in Rural Andhra Pradesh, India

We utilize data from a survey of approximately 400 rural households in Kurnool district of the southern Indian state of Andhra Pradesh. The survey, conducted during February-March 2005 in a cluster of 32 villages, was designed to obtain various household-level and individual-level information on production, consumption, asset holdings, time allocation, and several other economic aspects. Further details on survey design and objectives are found in Fuwa et al (2006a)[12].

The study region belongs to the semi-arid tropics of Deccan Plateau, notorious for high risk in agricultural production (Walker and Ryan 1990). The survey period of February-March is usually characterized by abundant demand for agricultural labor but the specific period of February-March 2005 experienced a drought, resulting in lower demand for farm labor. Nevertheless, we observed numerous instances of child labor. In addition, the state of Andhra Pradesh is a region with higher incidence of child labor than in other states of India.

For these reasons, our dataset covers sample households with higher incidence of child labor than found in other data sources in India. For instance, at the all India level (NSS dataset 1999/2000), the child labor incidence ratio among children aged 10-14 was 12.5% when a wider definition of child labor including household chores is used (Edmonds et al. 2005); in UP and Bihar (LSMS dataset 1997/98), where income poverty is more severe than in other regions of India, the child labor incidence ratio was reported to be around 28.3 percent (Sakamoto 2006); in our sample, the corresponding figure is 54.2 percent (Kurosaki et al. 2006).

4.2. Time Allocation of Children

Our survey contains a "one week time use module" whose reference period is the 7 days immediately prior to the interview date. The questionnaire asked the respondent about his/her activity in each "half-day" (AM or PM) during the reference period, so that a total of 14 half-days were classified as belonging to the following categories:

1) Remunerated work (including labor on own farm/enterprise)
2) Non-remunerated work
3) Household chores
4) Child care
5) Schooling
6) Social activities
7) Leisure
8) Sickness
9) Other, specify

Borrowing the classification in the ILO standards, we cover children in the age group 5-14 in

[11] We can elaborate an empirical framework without the assumption of multinormal distribution (Lee 1982). For example, Newey et al. (1990) proposed a procedure of nonparametric approximations for the sample selection correction terms. Yet, in general, these extensions provide comparable results to those derived under the joint normality assumption.

[12] We randomly selected sample households using a variable probability sampling method in order to collect a sufficient number of households containing child labor. In the statistical and econometric analyses of this paper, we corrected for the difference in the sampling probability by weighting. See Fuwa et al. (2006a) for details.

this paper. Table 1 summarizes the one week time use data for about one thousand children aged 5-14 included in the sample households. Among the nine categories mentioned above, we list *schooling* (category 5), *chores* (category 3), *child_care* (category 4), *rem_work* (category 1), and *leisure* (category 7). Child time use in each activity is measured as the number of half-days spent on that activity during the reference period, so that each variable takes on integer values between 0 and 14.

Table 1 shows some significant gender gaps in an expected manner. Boys spend significantly longer time on schooling and leisure than do girls, and girls spend significantly longer on domestic chores than do boys, and it appears that domestic chores are mainly done by teenage girls. On the other hand, child care is mainly done by younger (age 5-9) girls, who spend significantly longer hours than do boys of the same age group, but the gender gap in child care time is not significantly different from zero for teenage children. In neither age group, however, is there any evidence of a significant gender gap in the time spent on remunerative work (rem_work). Along the age lines, *schooling* and *leisure* time are longer among younger children than among older children, and older children spend more time working for the market than do younger children. This seems to indicate a tendency that girls spend more time in domestic works and both girls and boys spend more time as they grow, resulting in shorter time spent on schooling and leisure among older girls.

Since the mothers of these children also provide domestic work, we investigate the time use of children according to the working status of mothers (Table 2). Maternal employment is described by an indicator variable equal to one if there was at least one half-day of remunerative work during the reference period by a female household member having one or more children, regardless of whether or not she is the wife of the household head. Otherwise, the indicator takes on a value of zero.

Table 2 shows that except for the number of infants in the household and girls' time at remunerative work, there is no statistically significant difference between households with maternal employment and those without maternal employment, in terms of the number of children and child time use patterns. Girls in households with maternal employment spend significantly more time in remunerative work, whereas such tendencies are weaker and insignificant for boys. Also, the gender gaps in schooling and leisure seem to be greater under maternal employment than under no maternal employment. While these bivariate comparisons are suggestive, one of the main aims of this paper is to investigate further whether there is a direct causality between mothers' labor supply and the gender gap in children's time allocation.

4.3. Credit Constraints

The conventional empirical approach to incorporating credit constraints into an estimation model is to ignore the potential endogeneity of the constraints and to split the sample into those who are likely to be credit constrained and those who are not likely to be credit constrained exogenously (Zeldes 1989; Morduch 1990). This exogenous split approach, however, has two problems. First, it is unlikely that a single variable such as income-wealth ratio or land ownership is a good predictor of consumers' ability to borrow (Garcia et al. 1997, p.158; Jappelli 1990). Second, credit constraint is endogenously generated and thus should be treated as an endogenous variable. Otherwise, estimation results will likely suffer from endogeneity bias (Scott, 2000).

In order to overcome these problems, we designed the credit module carefully in our questionnaire so that we can identify credit-constrained households directly, as is suggested by Scott (2000). In identifying credit constraints, household heads were asked about members' experience with credit suppliers during the 12 months prior to the survey. To construct liquidity constraint indicators with sufficient variation across households, we decided to concentrate on formal credit sources. Our focus on formal credit derives from the following reasoning: First, a clear division between credit constrained and unconstrained households is likely to emerge in the context of bank or formal credit in the study region (Pender 1996), because access is often determined by the household's ability to provide collateral, which generally depends on ownership of land title; on the other hand, informal credit comes in numerous forms so that it is difficult to classify households according to credit access, and the determinants of access are less clear cut. The second reason for focusing on bank credit is that over the last few decades, formal sources of finance have become more accessible and important to the village economy in the study area. Given the increasing importance of formal credit, its impact on household behavior is interesting in itself.

To identify credit constrained households, we asked first whether a household tried to obtain a loan in a particular period. Then, for those who tried to borrow money, we asked whether a household could borrow as much as they requested. If the answer was yes, we identified the household as unconstrained. On the other hand, we identify those households who had their loan applications rejected, or could not borrow sufficiently as being credit constrained.

Second, for those who did not try to borrow, the enumerators asked the respondents about the reasons for not availing of a bank loan. The answer choices were:

1) No need for credit
2) Not want to be in debt
3) Terms are not attractive (duration too short, interest rate too high, etc.)
4) Too much paperwork
5) Live too far from lender
6) Already have large amount of debt
7) Believed I would be refused by lender
8) Don't know how to get credit / not know lender
9) Don't know anyone who can be guarantor
10) Other, specify

Respondents who chose one of the options 3)-9) as the reason for not attempting to obtain bank credit were identified as households likely to be credit-constrained with regard to formal sources. The remaining respondents who did not try to borrow can be considered to be unconstrained. We call this definition as the “broad definition of credit constraint.” However, respondents who chose one of the options 3)-5) might not in fact be credit-constrained, and we hence define an indicator variable under the “narrow definition of credit constraint,” identifying as constrained households choosing one of the options 6)-9). In our subsequent empirical analysis, we focus on this narrow definition of credit constraint. On the basis of these responses, we can identify the credit-constrained households who were *not able to* access credit. Since almost none of the existing multi-purpose household panel surveys include direct questions that identify credit constraints (Scott 2000), our data set provides us with valuable information directly to separate the constrained and unconstrained households.

Table 3 shows the descriptive statistics of all the 331 households used in this study. Among them, 164 households (or 49.5 percent) are identified to be credit-constrained (under the narrower definition), indicating that a significant proportion of households are indeed credit-constrained.[13] While the age and education profiles of the constrained and un-constrained households appear to be quite similar, the average household size is smaller, the average value of land owned is larger and the average per capita consumption is higher among un-constrained households than among constrained ones, although the difference is statistically significant only in the case of the average household size. Table 4 summarizes time use patterns of children of age groups 5-9 and 10-14 by contrasting credit constrained and unconstrained households. Schooling time is shorter, for both girls and boys and for both age groups, in credit constrained households relative to those in unconstrained households. The decline in the t-statistics appears to suggest that the gender gap in schooling may be smaller among credit constrained than in unconstrained households. In addition, younger girls’ time spent on

[13] Based on the ‘wider definition’ of credit constraint, 205 households (or 61.9 percent of the total) are identified as credit-constrained.

household chores increases and teenage boys' time on both chores and child care increases among credit constrained households than in unconstrained households. Time spent on remunerative work appears to be reduced among younger girls and teenage boys, while leisure time reduced by teenage children (both girls and boys), when household access to credit market is limited. We will investigate whether these observations based on the bivariate comparison hold when other factors are controlled for in a later section.

5. Empirical Results

5.1 Determinants of Children's Time Use: Estimation results of the reduced-form model

Explanatory Variables

In estimating the reduced form time use equation (14), the following independent variables are included: (1) Individual characteristics of a child: *age*, *agesq* (defined as (age-5)^2, to capture non-lineairty of the age effect), and *sex* (a dummy for a girl); (2) Household characteristics: *hd_age* (the age of the household head to control for the lifecycle effect), *f_edud* (the schooling dummy for the child's father), *m_edud* (the schooling dummy for the child's mother), their cross terms with *sex* to investigate the gender disparity among children, *hhsize* (the number of household members) and household composition (the shares of age-gender groups of household members, i.e., working-age male, *s_am,* working-age female, *s_af*, male children of age 5-14, *s_cm*, female children of age 5-14, *s_cf*, and children of age 0-4, *s_inf*), *bplhold* (a dummy variable for the ration card holder under the Public Distribution System of the Government of India), *landval* (the total amount of land owned by the household in 100,000 Rs., to control for the household's main asset), *acr_ir* (the acreage of irrigated land), *bullock_q* (the number of bullocks owned by the household, to represent the livestock asset), and dummy variables for communities (religion and wider caste groupings: *SC* [scheduled castes], *ST* [scheduled tribes], *UMH* [upper and medium Hindu castes], and *Muslim* [Muslims], with the reference category as those households belonging to so-called "other backward classes" [OBC]); (3) Potential shifters of household preferences through bargaining over intrahousehold resource allocation: *hdf_lit* (a dummy variable for literacy of the father of the household head), *hdm_lit* (a dummy variable for literacy of the mother of the household head), *spf_lit* (a dummy variable for literacy of the father of the spouse of the household head), *spm_lit* (a dummy variable for literacy of the mother of the spouse of the household head), *hdp_adiff* (the difference in age between the father and the mother of the household head), and *spp_adiff* (the difference in age between the father and the mother of the spouse of the household head). As McElroy (1990) argued, such extrahousehold environmental parameters (EEP) are likely to enter into reduced-form demand functions if preferences of men and women differ and their 'bargaining power' can be affected by such factors[14]; and (4) Village fixed effects, which collectively control for differences in market conditions, environments, and school qualities. 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 child labor and negative on enrollment. We will examine whether this holds 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.

---

[14] We have explicitly tested alternative models of household decision making (i.e., 'unitary' versus 'collective' models) with the same dataset in Fuwa et al (2006b).

[15] 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

Regression Results

Appendix Table 1 reports summary statistics of the empirical variables and Table 5 reports estimation results. Each column of Table 5 corresponds to a separate regression with each of the dependent variables: time spent on schooling (*schooling*), on leisure (*leisure*), on household chores (*chores*), on child care (*child_care*) and remunerative work (*rem_work*). The regression coefficients reported are based on ordinary least squares and with Huber-White robust standard errors.[16] Village and community dummies are also included, although the coefficients on village fixed effects are not reported for brevity.

There exist significant gender gaps in children's time allocation, even after controlling for (observable) household-level and individual-level characteristics. Girls' time for schooling and leisure is significantly shorter but girls' time for household chore and child care is significantly longer than boys.' The gender difference in *rem_work*, however, is not statistically significantly different from zero. The age effect is linearly positive on *rem_work* while it is concave on *schooling* and *convex* on leisure. The effect of parental education is in the direction of increasing schooling and decreasing child labor as documented in the existing empirical studies on India (Aggarwal 2004; Basu et al. 2003; Deb and Rosati 2002; Dr`eze and Kingdon 2001; Sakamoto 2006), but most of educational effects are insignificant in our dataset. Mothers' education significantly decreases *rem_work* but increases child care for both boys and girls. Fathers' education also increases girls' (but not boys') time on household chores. Among other household characteristics, the household demographic size (*hhsize*) has a negative effect on *rem_work*. Controlling for household size, an increase in the share of infants or male children significantly increases time child care and reduces leisure, while that of both adult and young female appears to reduce schooling. The coefficient on *landlval* is significantly positive on *schooling* and *leisure* and significantly negative on household chores. This is broadly consistent with the poverty effect hypothesis, but the insignificant coefficient on *rem_work* indicates that low wealth level, conditional on other covariates, is not a sufficient condition of child labor.[17]

The effects of the community dummies remain even after controlling for individual and household characteristics and village fixed effects. In the *rem_work* regression, coefficients on *ST*, *UMH*, and *Muslim* are negative and statistically significant, implying that households belonging to these groups are less likely to send children to remunerated work than households belonging to "other backward classes." In the *schooling* regression, the coefficient on *Muslim* is positive and statistically significant, implying that households belonging to Muslims are more likely to send children to school than households belonging to "other backward classes," which is opposite to our expectation and to the findings of Deb and Rosati (2002), Dr`eze and Kingdon (2001), Aggarwal (2004), and Sakamoto

---

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.

[16] Since our dependent variables are restricted to lie between zero and 14, an obvious alternative estimation method would be Tobit estimation to handle the censoring. We have also estimated two-sided tobit models, and found that their qualitative results are very similar to those based on OLS. As Deaton (1997, 85-89) has shown, with the presence of heteroskedasticity as well as censoring, tobit estimation does not necessarily perform better than OLS. In light of this, we report OLS results in text.

[17] These results were robust to the inclusion of other controls or dissaggregation of assets into its components such as land, building, livestock, etc. (Kurosaki et al. 2006). In South Asia, some authors find that farm land ownership is associated with more child labor because the productivity effect through family labor when wealth takes the form of land may dominate the usual wealth effect (so-called "wealth paradox": see Bhalotra and Heady 2003). One reason for the absence of the wealth paradox could be 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.

(2006). 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. Some (though not all) of the EEP coefficients are also significantly associated with time allocation of children. ***[interpretation?]***

5.2. Child Time Allocation and Credit Constraint

We now add the (endogenous) credit constraint variable to the reduced form equation estimated in the previous section. The main question of our interest is: how does access to credit affect the patterns of time allocation among children? We estimate a system of three equations: equation (15) for children's time use and equations (16) and (17) for the incidence of binding credit constraints. We use the land value (*landval*) as the identifying instrumental variable that is included as a determinant of credit access (K_h) but is excluded from the time use equations (15).

Determinants of Credit Constraint

The first stage regression results for the determinants of credit constraint are shown in Appendix Table 2. Among the explanatory variables, the market value of currently owned land (*landval*) has a significantly negative coefficient and the number of household members (*hhsize*) has a significantly positive coefficient. Therefore, households with fewer land assets and more household members are more likely to be under a binding credit constraint. This finding confirms in the multivariate context the casual finding in Table 3. Household demographic compositions also have significant coefficients. Coefficients on the share of children and infants (*s_cm*, *s_cf*, *s_inf*) tend to be positive and larger than those on the share of adult members, implying that younger households may be more likely to be credit-constrained. The coefficient on *bplhold* is also significantly positive, suggesting a possibility that the targeting in the PDS policy through distributing ration cards has been successful in identifying households with inferior access to credit beyond the extent indicated by the easily observable characteristics such as age, education and asset holdings.

Effects of Credit Constraint on Children's Time Allocation

Table 6 shows the intercept effects of credit constraint on child time allocation. Equation (15) is estimated together with equations (16) and (17) by a full information maximum likelihood method.[18] The estimated model includes all explanatory variables that were used in estimating the children's time use equations (as reported in Table 6), except for *landval*. The effect of credit constraint on *schooling* and *leisure* is negative with a very large and statistically significant coefficient (schooling or leisure time is reduced by about 2 to 3 days per week). Therefore, children in credit-constrained households are substantially worse off, suffering from the current low level of leisure and the future low level of income due to low schooling. Our results are broadly consistent with the recent empirical literature on the relationship between credit constraint and education (e.g., Edmonds (forthcoming), Jacoby (1994), Jacoby and Skoufias (1997)). On the other hand, the effects of credit constraint on *rem_work* and on household *chores* are not significantly different from zero. Rather surprisingly the effect of credit constraint is significantly negative on *child_care*. When the effects of endogenous credit access dummy are statistically significant, the null hypothesis that the two equations are independent is also rejected. Therefore, ignoring the endogeneity of credit constraint is likely to lead to biased inferences.

[18] When Equation (15) is estimated using Heckman=Lee's two-step estimation procedure, the results are very similar to those reported in Table 6.

5-3. Credit Constraint, Mothers' Work, and Children's Time Allocation

We are now in the position to address the main question: whether a increase in mothers' labor supply is likely to exacerbate gender disparities in children's time allocation, especially the gender gap in schooling, and whether such potential trade-offs between increasing mother's/women's labor supply and gender disparities are aggravated by credit constraints. We estimate a system of three equations: equation (20) for the determinants of mothers' work and equations (21a', 21b') for the intra-household difference in children's time use. In order to create the differenced dependent variable as in equation (21), we generate all possible girl-boy pairs within each household. Pairs are sorted so that the differences are taken in a specific order: namely, "girl minus boy." The parameter on maternal employment is allowed to vary by sex, so that the coefficient on maternal employment, *motwor*, measures the difference between the coefficient for girls and the coefficient for boys. According to our ordering rule, a positive coefficient on *motwor* can be interpreted as the girls' parameter on maternal employment being greater than the boys' parameter.[19]

In this specification, the only individual child characteristic that we include in the time use difference equation (20) is *d_age* (difference in age within the child pair). Among the household-level covariates, we include *s_inf* (the share of infants among the household members) as $\boldsymbol{X}_{hA}$ (household-level variables that appear both in equations (20) and (21a', b'). This is based on the observations found in the literature that infants requiring child care tend to affect more strongly the time use pattern of girls than that of boys (e.g., Pitt and Rosenzweig 1990). As $\boldsymbol{X}_{hB}$ (household-level variables that appear only in equation (20)), we include all other household-level variables.

Determinants of Mothers' Work

The first stage regression results for the determinants of mothers' work are shown in Appendix Table3. The education level of the child's mother increases the time of maternal employment, while that of the father has significantly negative effect.[20] The household demographic compositions are also significant predictors of mothers' time use. In contrast with the findings in developed countries where women with more school aged children and infants are less likely to work outside the household, our dataset shows that mothers with higher number of such children are more likely to work outside the household. The effect of *acr_ir* is also significantly positive, reflecting the tendency that mothers in more landed households spend more time working on their family farm. In other words, this effect shows that family labor and hired labor are incomplete substitutes in conducting farming operations.

The Gender Gap in Children's Time Allocation

Table 7 shows the estimation results of equations (21a') and (21b'). Rather surprisingly, the coefficients on (endogenous) mothers' labor supply ($\Delta\delta_{ij}$) are not significantly different from zero in most of the cases. Our results suggest that an increase in mothers' labor supply has small effects on the *gender gap* in time allocation between girls and boys. Nor is there any evidence that credit constraint has much effects on such potential trade-offs. The only exception is the effect of mothers' labor supply on the gender gaps in household chores within households *without* credit constraint. Among

[19] We intend to conduct a similar analysis using the full sample of all possible pairs of children, including those of siblings of same gender, in the near future.

[20] This is consistent with the findings in developed countries where more educated women are more likely to work outside the household.

[21]

households with sufficient access to credit, an increase in mothers' labor supply tends to significantly decrease the gender gap in household chores. This suggests that when mothers increase their labor supply, boys tend to disproportionately take over mothers' household chores. Such effect, however, is not observed for credit constrained households, which is rather puzzling.

It is generally encouraging to find that an increase in mothers' labor supply does not have significant effects on the gender gap in schooling. It is also worth noting, however, that our focus here is on the gender gap and not on the level of time use; while the gap between girls and boys in schooling are not affected it is possible that as mothers increase their labor supply their children could still reduce their schooling time to a similar extent between girls and boys.

The coefficient on *d_age* in the schooling equation is significantly negative, implying that the girl-boy schooling gap grows with the age difference between the two children, which in turn implies that older girls spend less time at school. In the case of child care, such effects of girl-boy age gaps are significant only among unconstrained households and not among credit constrained households. With other activities (except for child care), the magnitude of the 'age gap effects' on the gender gap in time allocation is similar between credit constrained and unconstrained households.

As we saw in bivariate comparisons, there are significant gender gaps in the time spent on schooling and household chore. However, our results in Table 7 (as well as Table 4) suggest that the gender gap in schooling is *smaller* among credit constrained households than are in unconstrained households. The intercept —which measures the gender gap after all the regressors are controlled for–– in the schooling equation (in Table 7) is significantly negative for unconstrained households, but the intercept is not statistically significantly different from zero for credit constrained households. The significant gender gap in schooling thus appears to vanish among credit constrained households. This is consistent with the case depicted in Figure 1 under the framework of Behrman et al (1982). That is, to the extent that boys are more 'educable' than are girls, parents appear to invest more of the household resources (including children's time) into boys' rather than girls' schooling, as their resource constraints are relaxed. Based on the model, this observation implies that the observed behavior of parents in our dataset exhibits relatively weak inequality aversion (toward the disparity in earnings between girls and boys) and that it is more consistent with the pure investment case, as documented by Rosenzweig and Schultz (1982). It should be noted, however, that this interpretation of parental behavior rests on a set of (rather strong) assumptions as discussed earlier. In addition, as Behrman (1988) found, the implied inequality aversion can differ substantially between the surplus season and the lean season and thus an observation in one point in time may not necessarily indicate a behavioral pattern that is stable overtime.[22]

In contrast, however, the opposite pattern is observed in the case of leisure; the significantly negative intercept for credit constraint households implies significantly shorter leisure time among girls within such households, but such effect is not observed among unconstrained households. So, girls in credit constrained households are significantly worse off, in terms of consumption of leisure, relative to boys in such households.

6. Conclusion

In this study, we utilized an original dataset to examine the effects of mothers' labor supply and credit constraint on children's time allocation with a recognition that all those variables are endogenous. Our data suggest strong evidence of gender disparity in children's time allocation. Even after controlling for individual and household-level characteristics, significant gender disparities remain in schooling time, domestic work and leisure. However there is no significant gender gap in the time spent on remunerative work. We also find that mothers' education reduces time spent on

[22] It may be argued, however, that schooling decision as we observe here may not be as variable across seasons as the allocation of nutrients among household members on which the study by Behrman (1988) is based.

remunerative work by both girls and boys. There is evidence that time spent by children for schooling and leisure is significantly shorter and time spent for domestic work significantly longer within households where credit constraint is binding.

In our analysis of focusing on the potential effects of increasing mothers' labor supply on the gender gap in children's time allocation, we find little evidence that such effects are quantitatively important within poor, credit constrained households. Despite the potential concern for mothers' dilemma that increasing mothers' labor hour could widen the gender gap in schooling, for example, through the possible increase in girls' time for domestic chore or child care, such possibilities are not supported by our empirical results. However, credit constraints do have significant effects on the gender gap in children's time allocation. We find that the gender gap in children's time allocation (esp. schooling) appears to be *smaller* in *credit-constrained* households than in unconstrained households. This is consistent with a possibility that parental aversion to inequality between girls' and boy's earnings is very weak and thus parents in our survey areas tend to enhance, rather than compensate, the differential endowments (which leads to differential labor market outcomes along the gender line) between girls and boys.

The implications for policy makers based on our empirical findings are threefold. First, encouraging women's labor market participation will be beneficial for poor households (as has been substantiated by the existing literature), and our results suggest that the potential negative effects on the *gender gap* in children's schooling appears to be negligible (although our analysis is unable to identify its effects on the *level* of children's schooling). Secondly, our data also provide an additional piece of evidence that encouraging female schooling will reduce child labor (among both girls & boys) Thirdly, however, our results have somewhat a nuanced implication for possible credit market policies. We find that facilitating credit access for the poor is likely to release children's time from domestic work for schooling, but it may also increase the gender disparity in schooling (as far as the returns to education are higher on boys than on girls). When attempts are made to increase access to credit by poor households, additional complementary measures to offset such potentials may be desirable. Gender targeted transfers aimed at encouraging girls schooling, such as the female stipend program implemented in Bangladesh, could be an example of such policy instruments.

References

Aggarwal, Surech Chand (2004), "Child Labour and Household Characteristics in Selected States: Estimates from NSS 55th Round." *Economic and Political Weekly*. January 10: 173-185.

Alderman, H., P.A. Chiappori, L. Haddad, J. Hoddinott, and R. Kanbur (1995) "Unitary versus Collective Models of the Household: Is it Time to Shift the Burden of Proof?" *World Bank Research Observer*, 10(1), pp.1-19.

Amemiya, Takeshi (1985), *Advanced Econometrics*, Harvard University Press.

Baland, Jean-Marie and James Robinson (2000), "Is Child Labour Inefficient?" *Journal of Political Economy* 108(4), 663-681.

Basu, Kaushik (1999), "Child Labor: Cause, Consequence, and Cure, with Remarks on International Labor Standards." *Journal of Economic Literature* 37, no. 3: 1083-119.

Basu, Kaushik; Sanghamitra Das; and Bhaskar Dutta (2003), "Birth-Order, Gender and Wealth as Determinants of Child Labour: An Empirical Study of the Indian Experience." Mimeo.

Basu, Kaushik, and Zafiris Tzannatos (2003), "The Global Child Labor Problem: What Do We Know and What Can We Do?" *World Bank Economic Review* 17, no. 2: 147-173.

Beegle, K. R. Dehajia, and R. Gatti (2003), "Child Labor, Crop Shocks, and Credit Constraints," NBER Working Paper No. 10088.

Behrman, J. R. (1988). "Intrahousehold Allocation of Nutrients in Rural India: Are boys favored? Do parents exhibit inequality aversion?" *Oxford Economic Papers* 40: 32-54.

----. (1997) "Intrahousehold Distribution and the Family." M.R. Rosenzweig and O. Stark (eds.) *Handbook of Population and Family Economics*. 125-187.

Behrman, J. R., R. A. Pollak and P. Taubman (1982). "Parental Preferences and Provision for Progeny." *Journal of Political Economy* 90: 52-73.

Behrman, J. R., R. A. Pollak and P. Taubman (1989). "Family Resources, Family Size, and Access to Financing for College Education." *Journal of Political Economy* 97: 398-419.

Bhalotra, Sonia, and Christopher Heady (2003), "Child Farm Labor: The Wealth Paradox." *World Bank Economic Review* 17, no. 2: 197-227.

Browning, M. and P.A. Chiappori (1998) "Efficient Intra-Household Allocations: A General Characterization and Empirical Tests," *Econometrica* 66(6), pp.1241-78.

Deb, P., and F. Rosati (2002), "Determinants of Child Labor and School Attendance: The Role of Household Unobservables." Mimeo. Understanding Children's Work: An Inter-Agency Research Cooperation Project. ILO/UNICEF.

Deaton, A. (1997), *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*. World Bank.

Doss, C. (1996) "Testing among Models of Intrahousehold Resource Allocation," *World Development*. 24(10), pp.1597-1609.

Dr`eze, Jean, and Geeta Gandhi Kingdon (2001), "School Participation in Rural India." *Review of Development Economics* 5 no. 1: 1-24.

Durand, John D. (1975), *The Labor Force in Economic Developmen,*, Princeton: Princeton University Press.

Edmonds, E. (forthcoming). "Child Labor and Schooling Responses to Anticipated Income in South Africa." *Journal of Development Economics*. (in press)

Edmonds, E., N. Pavcnik. and P. Topalova (2005) "Trade Liberalization, Child Labor, and Schooling: Evidence from India." Paper presented at the NEUDC (Northeast Universities Development Consortium Conference) 2005, Brown University, Providence.

Fuwa, N., S. Ito, K. Kubo, T. Kurosaki, and Y. Sawada (2006a) "An Introduction to a Study of Intrahousehold Resource Allocation and Gender Discrimination in Rural Andhra Pradesh, India," *Developing Economies* 44(4) in printing.

----- (2006b), "Gender Discrimination, Intrahousehold Resource Allocation, and Importance of Spouse's Fathers: Evidence on Household Expenditure from Rural India," *Developing Economies* 44(4) in printing.

Garcia, R., A. Lusardi, and S. Ng (1997), "Excess Sensitivity and Asymmetries in Consumption: An Empirical Investigation," *Journal of Money, Credit, and Banking* 29(2), 154-176.

Garg, A. and J. Morduch (1998), "Sibling Rivalry and the Gender Gap: Evidence from Child Health Outcome in Ghana," *Journal of Population Economics* 11(4), 471-93.

Goldin, C. (1995), "The U-Shaped Female Labor Force Function in Economic Development and

Economic History," T. Paul Shultz ed., *Investment in Women's Human Capital*, University of Chicago Press.
ILO-IPEC (2005), *Combating Child Labour in Asia and in the Pacific: Progress and Challenges*. ILO-IPEC.
Ilahi, Nadeem. (2000). The Intra-household Allocation of Time and Tasks: What have we learnt from the empirical literature? Washington, D.C.: World Bank Policy Research Report on Gender and Development Working Paper Series No. 13.
Ito, T. and T. Kurosaki (2006) "Weather Risk and the Off-Farm Labor Supply of Agricultural Households in India," paper presented at the International Association of Agricultural Economists Conference, Gold Coast, Australia, August 12-18, 2006.
Jacoby, H.(1994), "Borrowing Constraints and Progress through School: Evidence from Peru," *Review of Economics and Statistics*, 76, 151-160.
Jacoby, H. and E. Skoufias (1997), "Risk, Financial Markets and Human Capital in Developing Countries," *Review of Economic Studies* 64, 311-335.
Jappelli, T. (1990), "Who Is Credit-Constrained in the U.S. Economy?" *Quarterly Journal of Economics* 105 (1), 219-234.
Kochar, A. (1999), "Smoothing Consumption by Smoothing Income: Hours-of-Work Responses to Idiosyncratic Agricultural Shocks in Rural India," *Review of Economics and Statistics* 81(1), 50-61.
Kurosaki, Takashi, Seiro Ito, Nobuhiko Fuwa, Kensuke Kubo, Yasuyuki Sawada (2006), "Child Labor and School Enrollment in Rural India: Whose Education Matters?" *Developing Economies* 44(4) in printing.
Lee, Lung-Fei (1982), "Some Approaches to the Correction of Selectivity Bias," *Review of Economic Studies* 49, 355-372.
Lieten, G.K. (2002) "Child Labour in India: Disentangling Essence and Solutions." *Economic and Political Weekly*. December 28: 5190-5195.
Lundberg, S., R. Pollak, and T. J. Wales. (1997). "Do Husbands and Wives Pool Their Resources? Evidence from the U.K. child benefit" *Journal of Human Resources* 32: 463-480.
Maddala, G. S. (1983), *Limited-Dependent and Qualitative Variables in Econometrics*, Cambridge University Press.
Mammen, K. and C. Paxson (2000), "Women's Work and Economic Development," *Journal of Economic Perspectives* 14(4), 141-164.
McElroy, M. (1990), "The Empirical Content of Nash-bargained Household Behavior." *Journal of Human Resources* 25: 559-583.
Morduch, J. (1990), "Risk, Production and Saving: Theory and Evidence from Indian Households, " mimeo, Harvard University.
Morduch, J. (1994), "Poverty and Vulnerability," *American Economic Review*, AEA Papers and Proceedings, 84 (2), 221-225.
Newey, Whitney K., James L. Powell, and James R. Walker (1990), "Semiparametric Estimation of Selection Models: Some Empirical Results," *American Economic Review* 80(2), 324-328.
Pender, John L. (1996), "Discount Rates and Credit Markets: Theory and Evidence from Rural India," *Journal of Development Economics* 50, 257-296.
Pitt, Mark (1997). "Specification and Estimation of the Demand for Goods within the Households." in Lawrence Haddad, John Hoddinott, and Harold Alderman (eds.). *Intrahousehold Resource Allocation in Developing Countries: Models, methods, and policy*. Baltimore and London: The Johns Hopkins University Press.
Pitt, Mark and Mark Rosenzweig (1990), "Estimating the Intrahousehold Incidence of Illness: Child Health and Gender-Inequality in the Allocation of Time," *International Economic Review* 31, 969-989.
Pollak, Robert (1969). "Conditional Demand Functions and Consumption Theory." *Quarterly Journal of Economics*, 83: 1. 60-78.
Quisumbing, Agnes R., and Maluccio, John A. (2000), "Intrahousehold Allocation and Gender Relations: New Empirical Evidence from Four Developing Countries." FCND Discussion Paper No. 84, April 2000, Washinton D. C.: IFPRI (International Food Policy Research Institute).
----- (2003), "Resources at Marriage and Intrahousehold Allocation: Evidence from Bangladesh, Ethiopia, Indonesia, and South Africa," *Oxford Bulletin of Economics and Statistics* 65, no. 3: 283-327.

Sakamoto, Shunsuke (2006), "Parental Attitudes toward Children and Child Labor: Evidence from Rural India," Hi-Stat Discussion Paper, No.05-136, Hitotsubashi University.
Sawada, Yasuyuki, Kensuke Kubo, Nobuhiko Fuwa, Seiro Ito, and Takashi Kurosaki (2006), "On the Mother and Child Labor Nexus under Credit Constraints: Findings from Rural India," *Developing Economies* 44(4) in printing.
Scott, Kinnon (2000), “Credit,” in Margaret Grosh and Paul Glewwe, eds., *Designing Household Survey Questionnaires for Developing Countries: Lessons from Ten Years of LSMS Experience*, Volume Two, the World Bank.
Skoufias, Emmanuel (1993). “Labor Market Opportunities and Intrafamily Time Allocation in Rural Households in South Asia.” *Journal of Development Economics* 40, 277-310.
---- (1996). “Intertemporal Substitution in Labor Supply: Micro Evidence from Rural India,” *Journal of Development Economics* 51, 217-237.
Thomas, Duncan (1990). “Intra-household Resource Allocation: an inferential approach.” *Journal of Human Resources* 29: 635-664.
---- (1994). "Like Father, Like Son; Like Mother, Like Daughter: Parental Resources and Child Height." *Journal of Human Resources* 29, no. 4: 950-988.
Walker, T.S. and J.G. Ryan (1990) *Village and Household Economies in India's Semi-arid Tropics*. Baltimore: Johns Hopkins University Press.
Zeldes, S. P. (1989), “Consumption and Liquidity Constraints: An Empirical Investigation,” *Journal of Political Economy* 97, 305-346.

Table 1: Time Use of Children in the Sample Households, Andhra Pradesh, India, 2005

	Aged 5-9			Aged 10-14		
	Boys	Girls	*t* test for the same mean	Boys	Girls	*t* test for the same mean
No. of Obs. (NOB)	198	196	(d.o.f.=392)	312	296	(d.o.f.=606)
schooling	5.869	4.541	2.646	3.455	2.652	2.135
	(5.018)	(4.941)	*0.009*	(4.888)	(4.353)	*0.033*
chores	0.066	0.740	-3.630	0.317	2.145	-7.282
	(0.571)	(2.550)	*0.000*	(1.427)	(4.185)	*0.000*
child_care	0.121	1.102	-3.584	0.147	0.189	-0.351
	(1.182)	(3.663)	*0.000*	(1.386)	(1.544)	*0.726*
rem_work	0.808	1.077	-0.823	4.356	4.791	-0.898
	(3.032)	(3.433)	*0.411*	(5.981)	(5.957)	*0.370*
leisure	5.621	4.740	1.764	2.750	1.649	3.901
	(4.912)	(5.009)	*0.079*	(3.970)	(2.874)	*0.000*

Notes: Numbers above show averages or t-statistics. Numbers in parenthesis below show standard deviations and italic numbers below show p-values.

Table 2: Characteristics of Mothers and Time Use of Children Aged 5-14 by their Working Status

		Non-working mothers/1	Working mothers/1	The mother is not in the household	*t*-statistic for the same mean: (1) and (2)
		(1)	(2)	(3)	(4)
NOB		150	237	29	
Number of daughters aged 5-14		1.227	1.228	0.759	-0.011
		(0.977)	(1.053)	(0.786)	*0.991*
Number of sons aged 5-14		1.260	1.257	1.000	0.029
		(0.839)	(0.896)	(0.964)	*0.977*
Number of infants aged 0-4		0.667	0.477	-	2.027
		(0.953)	(0.861)	-	*0.043*
Time use of children aged 5-14 (unit: half-days)					
schooling	girl	3.709	3.298	2.824	0.791
		(4.569)	(4.094)	(4.202)	*0.430*
	boy	4.099	4.731	3.967	-1.132
		(4.927)	(4.806)	(4.510)	*0.259*
chores	girl	1.742	1.544	1.235	0.526
		(3.256)	(2.998)	(2.751)	*0.599*
	boy	0.343	0.177	0.000	1.385
		(1.197)	(0.935)	(0.000)	*0.167*
child_care	girl	0.515	0.640	0.088	-0.440
		(2.013)	(2.521)	(0.364)	*0.661*
	boy	0.074	0.121	0.000	-0.533
		(0.656)	(0.837)	(0.000)	*0.594*
rem_work	girl	2.020	3.990	5.147	-3.429
		(0.398)	(0.382)	(6.025)	*0.001*
	boy	2.955	3.245	2.317	-0.513
		(0.430)	(0.362)	(4.179)	*0.608*
leisure	girl	3.239	2.751	2.176	1.067
		(4.041)	(3.589)	(2.531)	*0.287*
	boy	3.497	3.778	4.117	-0.614
		(3.881)	(4.038)	(4.116)	*0.540*
Working time of fathers of children aged 5-14 (unit: half-days)		5.101	7.430	6.667	-3.816
		(5.541)	(5.379)	(6.154)	*0.000*

Notes: (1) Numbers above show averages or t-statistics. Numbers in parenthesis below show standard deviations and italic numbers below show p-values.
(2) For fathers and mothers, "working" includes remunerative works including working for self-employment business (farm and non-farm) but excludes domestic chores and child care.

Table 3: Characteristics of the Sample Households by their Credit Constraint Status

	Credit constraint not binding	Under binding credit constraint	*t*-statistic for the same mean
Wider definition of credit constraints (*cc*1)			
NOB	126	205	
hd_age (age of the household head)	44.540	44.371	0.137
	(0.999)	(0.743)	*0.891*
hd_edu (schooling years of the hh head)	1.706	1.746	-0.111
	(0.281)	(0.224)	*0.912*
sp_edu (schooling years of the hh head's spouse)	0.619	0.590	0.135
	(0.161)	(0.135)	*0.893*
hhsize (number of household members)	7.214	7.810	-1.390
	(0.244)	(0.300)	*0.165*
landval (value of land owned by the household in 100,000Rs)	1.432	0.794	1.846
	(0.411)	(0.098)	*0.066*
cons (per capita consumption per week in Rs.)	142.384	140.106	0.134
	(10.449)	(11.662)	*0.893*
Narrower definition of credit constraints (*cc*2)			
NOB	167	164	
hd_age (age of the household head)	44.263	44.610	-0.290
	(0.834)	(0.854)	*0.772*
hd_edu (schooling years of the hh head)	1.832	1.628	0.584
	(0.253)	(0.241)	*0.560*
sp_edu (schooling years of the hh head's spouse)	0.623	0.579	0.210
	(0.143)	(0.150)	*0.834*
hhsize (number of household members)	7.162	8.012	-2.052
	(0.213)	(0.358)	*0.041*
landval (value of land owned by the household in 100,000Rs)	1.240	0.829	1.223
	(0.314)	(0.113)	*0.222*
cons (per capita consumption per week in Rs.)	145.693	136.167	0.578
	(9.988)	(13.167)	*0.564*

Notes: Numbers above show averages or t-statistics. Numbers in parenthesis below show standard deviations and italic numbers below show p-values.

Table 4: Time Use of Children and Household's Credit Access Status

Age 5-9

		Credit constrained	*t*-statistic for the same mean: boys and girls	Un-constrained	*t*-statistic for the same mean: boys and girls
		(1)	(2)	(3)	(4)
schooling	girl	4.4778	1.6721	4.5773	2.126
	boy	5.7263		6.0909	
chores	girl	1.0222	3.1387	.4742	1.6657
	boy	0.0737		.0682	
child_care	girl	1.0889	2.4654	1.0722	2.2687
	boy	.1053		.15909	
rem_work	girl	.6667	.5428	1.4742	1.278
	boy	.9053		.7955	
leisure	girl	4.7333	1.3205	4.7732	.8635
	boy	5.7263		5.375	

Age 10-14

		Credit constrained	*t*-statistic for the same mean: boys and girls	Un-constrained	*t*-statistic for the same mean: boys and girls
		(1)	(2)	(3)	(4)
schooling	girl	2.5303	1.474	2.7664	1.803
	boy	3.3869		3.7714	
Chores	girl	2.2273	4.2722	2.0730	5.2859
	boy	.5401		.1786	
child_care	girl	.1894	.527	.2044	1.435
	boy	.3066		0	
rem_work	girl	4.8030	1.1807	4.6934	0.0008
	boy	3.9635		4.6929	
leisure	girl	1.25	2.7811	1.9635	2.2193
	boy	2.3696		2.9071	

Table 5: Determinants of Children's Time Use (OLS estimation results of the reduced-form model)

	schooling		*chores*		*child care*		*rem_work*		*leisure*	
	Coeff.	Std.error	Coeff.	Std.error	Coeff.	Std.error	Coeff.	Std.error	Coeff.	Std.error
age	0.248	(0.242)	0.116	(0.136)	0.134	(0.122)	0.752	(0.244)***	-1.789	(0.257)***
agesq	-0.078	(0.024)***	0.013	(0.016)	-0.014	(0.012)	0.006	(0.027)	0.113	(0.025)***
sex	-1.524	(0.421)***	1.394	(0.279)***	1.024	(0.305)***	0.513	(0.531)	-1.312	(0.478)***
hd_age	0.006	(0.020)	-0.002	(0.015)	-0.005	(0.014)	0.009	(0.023)	0.003	(0.019)
f_edud	-0.082	(0.087)	0.042	(0.035)	-0.004	(0.031)	-0.049	(0.103)	-0.095	(0.083)
*f_edud*sex*	-0.006	(0.100)	0.200	(0.101)**	-0.076	(0.052)	-0.105	(0.141)	0.057	(0.112)
m_edud	0.185	(0.211)	0.070	(0.076)	0.100	(0.043)**	-0.232	(0.135)*	0.002	(0.148)
*m_edud*sex*	0.108	(0.249)	-0.174	(0.140)	-0.072	(0.060)	0.185	(0.184)	0.168	(0.178)
hhsize	0.028	(0.051)	-0.023	(0.029)	0.044	(0.048)	-0.143	(0.075)*	0.078	(0.059)
s_am	-0.035	(0.027)	0.017	(0.022)	0.023	(0.016)	0.014	(0.037)	-0.046	(0.031)
s_af	-0.060	(0.029)**	0.020	(0.022)	-0.000	(0.011)	-0.022	(0.037)	-0.012	(0.032)
s_cm	-0.033	(0.028)	0.022	(0.021)	0.035	(0.013)***	0.037	(0.034)	-0.064	(0.030)**
s_cf	-0.047	(0.028)*	0.029	(0.021)	0.009	(0.012)	0.004	(0.033)	-0.043	(0.029)
s_inf	-0.042	(0.029)	0.002	(0.022)	0.072	(0.025)***	-0.015	(0.043)	-0.121	(0.032)***
landval	0.073	(0.033)**	-0.065	(0.024)***	0.005	(0.220)	-0.054	(0.050)	0.090	(0.043)**
acr_irr	-0.001	(0.006)	-0.003	(0.005)	-0.002	(0.003)	0.001	(0.010)	0.017	(0.007)***
bullock_q	0.150	(0.220)	0.006	(0.175)	0.027	(0.171)	0.391	(0.267)	-0.744	(0.208)***
bplhold	0.636	(0.437)	0.753	(0.323)**	-0.235	(0.357)	-0.767	(0.539)	-0.283	(0.495)
hdf_lit	1.999	(0.461)***	0.138	(0.358)	0.671	(0.365)*	-1.571	(0.574)***	0.166	(0.474)
hdm_lit	-2.079	(1.244)*	0.850	(0.869)	-1.098	(0.439)***	-1.113	(0.914)	0.634	(0.962)
spf_lit	-0.543	(0.436)	-1.004	(0.303)***	-0.245	(0.219)	-0.794	(0.539)	0.250	(0.444)
spm_lit	-0.908	(1.401)	2.615	(1.822)	-1.460	(1.050)	2.845	(1.398)**	-1.937	(1.452)
hdp_adiff	-0.131	(0.050)***	-0.008	(0.036)	-0.024	(0.030)	0.040	(0.057)	-0.022	(0.050)
spp_adiff	0.158	(0.520)***	0.003	(0.032)	-0.018	(0.044)	0.011	(0.056)	-0.082	(0.054)
SC	0.389	(0.465)	-0.110	(0.352)	-0.235	(0.242)	-0.534	(0.599)	0.162	(0.519)
ST	-1.350	(1.033)	1.961	(0.655)	0.012	(0.264)	-4.429	(1.805)**	0.931	(1.596)
UMH	1.752	(1.125)	-0.639	(1.036)***	0.087	(0.383)	-2.749	(0.845)***	0.968	(1.378)

Muslim	1.649	(0.910)*	0.308	(0.772)	0.243	(0.772)	-2.109	(0.883)**	-2.538	(0.848)***
constant	6.349	(3.135)**	-4.230	(2.298)*	-2.897	(1.558)*	-3.062	(3.544)	23.841	(3.467)***
NOB	779		779		779		779		779	
F (59, 719) for zero slope	11.88		1.78		0.47		5.01		6.97	
R2	0.321		0.212		0.150		0.264		0.319	

Notes (1) Statistically significant at 1% (***), 5% (**), 10% (*) [same in the following tables].
(2) All models include village fixed effects. The village fixed effects are jointly statistically-significant at the 1% level (not reported to save space).

Table 6: Effects of Credit Access on Children's Time Use (Type 5 Tobit estimation results)

	schooling		*chores*		*child care*		*rem_work*		*leisure*	
	Coeff.	Std.error	Coeff.	Std.error	Coeff.	Std.error	Coeff.	Std.error	Coeff.	Std.error
cc_b2	**-5.503**	**(1.701)*****	**0.273**	**(1.318)**	**-3.280**	**(0.453)*****	**0.918**	**(0.861)**	**-4.612**	**(1.880)*****
age	0.319	(0.234)	0.103	(0.131)	0.080	(0.096)	0.735	(0.240)***	-1.818	(0.250)***
agesq	-0.085	(0.023)***	0.015	(0.015)	-0.008	(0.009)	0.009	(0.027)	0.116	(0.024)***
sex	-1.621	(0.404)***	1.426	(0.271)***	0.902	(0.241)***	0.606	(0.522)	-1.298	(0.449)***
hd_age	0.023	(0.021)	-0.002	(0.014)	-0.004	(0.015)	0.011	(0.023)	0.003	(0.020)
f_edud	-0.128	(0.089)	0.031	(0.035)	-0.003	(0.040)	-0.085	(0.103)	-0.081	(0.084)
*f_edud*sex*	0.041	(0.097)	0.154	(0.093)*	-0.086	(0.044)*	-0.087	(0.142)	0.031	(0.109)
m_edud	0.309	(0.201)	0.084	(0.075)	0.140	(0.073)*	-0.228	(0.137)*	0.042	(0.160)
*m_edud*sex*	0.079	(0.235)	-0.158	(0.131)	-0.044	(0.047)	0.186	(0.181)	0.181	(0.168)
hhsize	0.106	(0.051)**	-0.034	(0.034)	0.095	(0.054)*	-0.155	(0.071)**	0.146	(0.061)**
s_am	0.001	(0.032)	0.010	(0.021)	0.025	(0.017)	0.013	(0.037)	-0.037	(0.033)
s_af	-0.024	(0.034)	0.013	(0.022)	0.021	(0.017)	-0.038	(0.036)	0.025	(0.035)
s_cm	-0.025	(0.031)	0.018	(0.023)	0.053	(0.017)***	-0.006	(0.034)	-0.030	(0.034)
s_cf	0.014	(0.032)	0.023	(0.022)	0.036	(0.015)**	-0.007	(0.033)	-0.004	(0.034)
s_inf	0.022	(0.034)	-0.005	(0.025)	0.109	(0.030)***	-0.030	(0.043)	-0.072	(0.038)*
acr_irr	0.057	(0.040)	0.019	(0.034)	-0.009	(0.026)	-0.032	(0.050)	0.059	(0.046)
bullock_q	0.145	(0.240)	-0.013	(0.161)	0.053	(0.177)	0.398	(0.263)	-0.639	(0.228)***
bplhold	1.269	(0.579)**	0.769	(0.410)*	0.564	(0.347)	-1.000	(0.563)*	-0.621	(0.576)
hdf_lit	2.520	(0.532)***	0.187	(0.347)	0.654	(0.395)*	-1.465	(0.576)**	0.192	(0.486)
hdm_lit	-2.895	(1.871)*	1.022	(0.888)	-1.444	(0.644)***	-1.065	(0.949)	0.651	(0.986)
spf_lit	-0.771	(0.509)	-1.161	(0.280)***	-0.157	(0.258)	-0.885	(0.541)	0.501	(0.463)
spm_lit	-0.453	(1.514)	2.624	(1.642)	-0.359	(0.800)	2.860	(1.164)**	-1.390	(0.937)
hdp_adiff	-0.170	(0.058)***	0.005	(0.035)	-0.065	(0.031)**	0.064	(0.057)	-0.071	(0.053)
spp_adiff	0.161	(0.058)***	-0.025	(0.031)	-0.031	(0.036)	0.019	(0.055)	-0.031	(0.055)
SC	0.912	(0.544)*	-0.248	(0.353)	-0.004	(0.301)	-0.649	(0.592)	0.647	(0.608)
ST	-0.032	(1.309)	1.861	(0.739)**	1.051	(0.415)**	-4.573	(1.710)***	2.190	(1.741)

UMH	0.888	(1.189)	-0.689	(0.924)	-0.305	(0.515)	-2.862	(0.871)***	0.851	(1.468)
Muslim	2.495	(1.135)**	0.184	(0.837)	0.899	(0.794)	-2.084	(0.844)**	-1.533	(0.965)
constant	2.584	(3.337)	-3.499	(2.202)	-3.881	(1.716)***	-2.265	(3.425)	22.119	(3.404)***
NOB	754		754		754		754		754	
Chi2 for zero slope	625.9		109.32		118.71		326.06		383.61	
R2										

Notes: (1) Simultaneous estimation using the maximum likelihood estimation. NOB=754. "chi2(1) shows the Wald test statistics for the null that the two equations are independent.

(2) b_cc2 is an endogenous variable. All models include all explanatory variables listed on Table 6 (except for landval, which is dropped for the identification purpose). Village and community fixed effects are also included. Weighted linear models are estimated to correct for the difference in sampling probability.

Table 7: Effects of Mother's Working Time on Children's Time Use with/without Credit Constraint (2SLS)

	schooling		*chores*		*child care*		*rem work*		*leisure*	
	cc=1	*cc*=0	*cc*=1	*cc*=0	*cc*=1	*cc*=0	*cc*=1	*cc*=0	*cc*=1	*cc*=0
($\Delta\delta_{ij}$)*moth_work*	0.0039	0.0905	0.0790	0.1336**	0.0084	0.0215	-0.0844	0.1931	0.0227	0.0392
	(0.070)	(0.070)	(0.061)	(0.053)	(0.050)	(0.025)	(0.099)	(0.120)	(0.095)	(0.107)
(α_j)*d_age*	-0.4807***	-0.5560***	-0.2628***	-0.2481***	-0.1076	-0.0655*	0.8437***	1.0245***	-0.5722***	-0.6784***
	(0.109)	(0.096)	(0.068)	(0.085)	(0.065)	(0.036)	(0.1229)	(0.156)	(0.110)	(0.137)
($\Delta\alpha_{ij}$)*infants*	-0.0226	0.0376	-0.0954***	-0.0595*	0.1167***	0.1067**	0.0827	-0.0567	0.0241	0.0007
	(0.036)	(0.042)	(0.027)	(0.031)	(0.039)	(0.042)	(0.067)	(0.081)	(0.043)	(0.053)
Mill's ratio	-0.8032	-0.3114	-1.8866***	-0.7742	0.2058	0.5584	1.9659	0.7425	1.3935	1.6407
	(1.111)	(0.817)	(0.665)	(0.907)	(0.852)	(0.352)	(1.329)	(1.524)	(1.162)	(1.327)
Constant	-0.3368	-2.8700***	2.8955***	2.3984***	-0.1067	0.1184	-0.8046	0.7155	-2.3907***	-0.2632
	(0.957)	(0.837)	(0.662)	(0.777)	(0.741)	(0.269)	(1.207)	(1.631)	(0.764)	(1.414)
NOB	229	207	229	207	229	207	230	207	229	207
R-squared	0.1254	0.1509	0.1327	0.0632	0.1111	0.1536	0.2373	0.2482	0.1728	0.1723

Notes: (1) Heteroscedasticity-robust standard errors are shown in parenthesis.
(2) Since motwor is an endogenous variable, the weighted 2SLS estimation method was applied with the Model in Appendix Table 2 as the 1st stage estimation. Weighted regressions were adopted to correct for the difference in sampling probability.

Parental preferences with weak inequality aversion

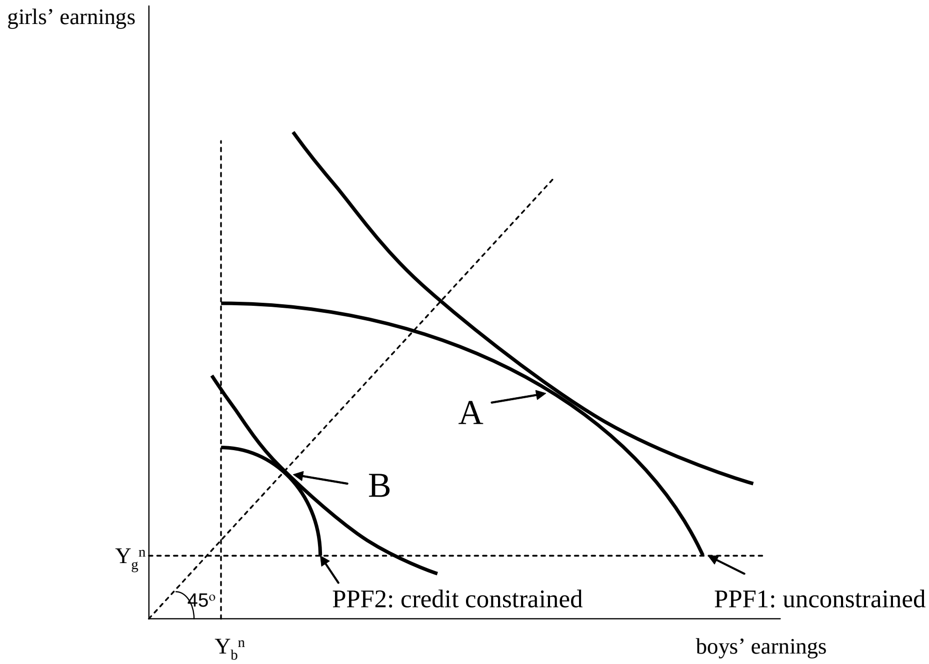

Figure 1

Parental preferences with strong inequality aversion

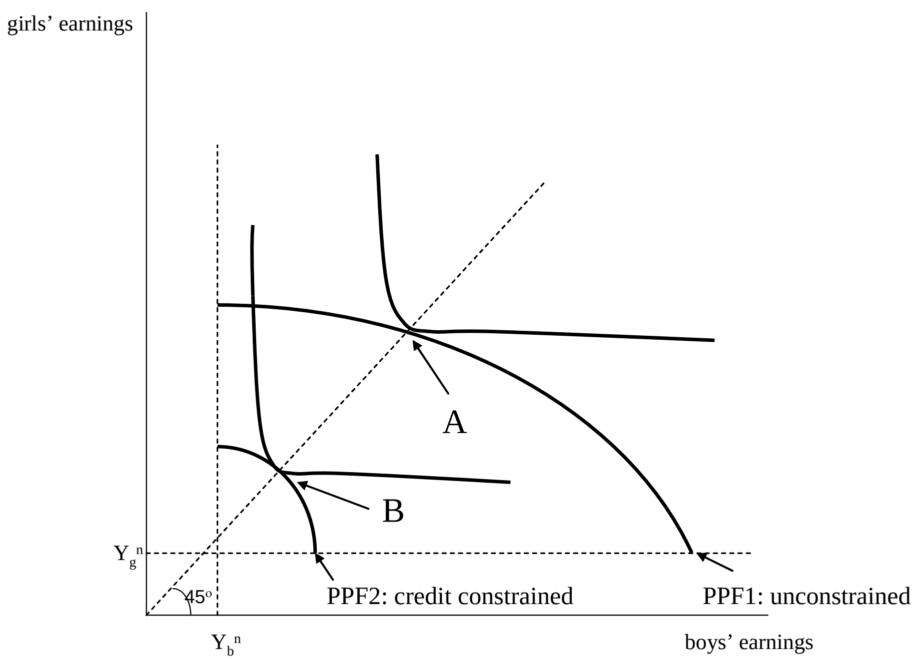

Figure 2

Appendix table 1: Definition and Summary Statistics of Variables

Name	Definition (unit)	NOB	Mean	Std.Dev.	Min.	Max.
Endogenous variables, child-level						
schooling	Time used in schooling and study (half-days)	1002	3.339	4.677	0	14
chores	Domestic chores (half-days)	1002	0.970	2.941	0	14
child_care	Care of small children (half-days)	1002	0.487	2.475	0	14
dom_work	*chores* + *child_care*	1002	1.457	3.749	0	14
rem_work	Remunerative work (half-days)	1002	3.311	5.473	0	14
leisure	Leisure time (half-days)	1002	3.612	4.650	0	14
Exogenous variables, child-level						
age	Age of the child	1002	10.061	2.677	5	14
agesq	(*age*-5)^2	1002	32.774	26.541	0	81
sex	Dummy for a girl	1002	0.497	dummy	0	1
Endogenous variables, household-level						
motwor	Remunerative work by the mother (half-days)	385	5.772	5.612	0	14
*cc*1	Credit constraint dummy (wider definition)	368	0.620	dummy	0	1
*cc*2	Credit constraint dummy (narrower definition)	368	0.509	dummy	0	1
Exogenous variables, household-level						
hd_age	Age of the household head	387	44.45	10.90	20	82
f_edud	Schooling dummy for the father of children aged 5-14	335	0.279	dummy	0	1
m_edud	Schooling dummy for the mother	383	0.114	dummy	0	1
hhsize	Number of household members	387	7.906	4.550	3	29
s_am	# of adult males (15-60)/*hhsize* (%)	387	25.31	11.78	0	66.67
s_af	# of adult females (15-60)/*hhsize* (%)	387	23.72	10.05	0	66.67
s_cm	# of boys (5-14)/*hhsize* (%)	387	19.94	13.02	0	66.67
s_cf	# of girls (5-14)/*hhsize* (%)	387	19.56	14.76	0	75.00
s_inf	# of infants (0-4)/*hhsize* (%)	387	6.62	9.56	0	37.50
infants	Number of infants (0-4)	387	0.655	1.017	0	5
landval	Value of land owned by the household (100,000Rs)	387	0.966	2.585	0	48
acr_irr	Acreage of irrigated land operated by the household (acres)	387	3.615	30.773	0	500
bullock_q	Number of bullocks owned by the household	387	0.871	1.031	0	4
bplhold	Dummy for the receipt of a ration card for Below-the-Poverty-Line (BPL) households under the Public Distribution System	387	0.728	dummy	0	1
hdf_lit	Literacy dummy for the father's father	376	0.236	0.425	0	1
hdm_lit	Literacy dummy for the father's mother	376	0.017	0.131	0	1

spf_lit	Literacy dummy for the mother's father	385	0.212	0.410	0	1
spm_lit	Literacy dummy for the mother's mother	385	0.012	0.108	0	1
hdp_adiff	Age difference between the father's parents	375	4.911	4.599	0	30
spp_adiff	Age difference between the mother's parents	379	4.621	4.662	0	25
OBC	Other backward classes (reference)	387	0.685	dummy	0	1
SC	Scheduled castes	385	0.177	dummy	0	1
ST	Scheduled tribes	385	0.056	dummy	0	1
UMH	Upper and middle Hindu castes	385	0.038	dummy	0	1
Muslim	Muslim	385	0.043	dummy	0	1

Note: Weighted averages to correct for the difference in sampling probability.

Appendix Table 2: Determinants of Binding Credit Constraints (probit estimation results)

	Narrower definition (*cc*2)		
	dF/dX*	Std.error	
hd_age	-0.0031	(0.0024)	
f_edud	-0.0032	(0.0083)	
m_edud	-0.0039	(0.0165)	
hhsize	0.0193	(0.0065)	***
s_am	0.0090	(0.0040)	**
s_af	0.0095	(0.0039)	**
s_cm	0.0132	(0.0036)	***
s_cf	0.0118	(0.0035)	***
s_inf	0.0146	(0.0043)	***
landval	-0.0386	(0.0211)	*
acr_ir	0.0049	(0.0057)	
bullock_q	0.0685	(0.0290)	**
bplhold	0.1750	(0.0604)	***
hdf_lit	0.0317	(0.0593)	
hdm_lit	-0.0787	(0.1958)	
spf_lit	0.0879	(0.0542)	
spm_lit	-0.3194	(0.1874)	
hdp_adiff	-0.0041	(0.0062)	
spp_adiff	-0.0040	(0.0065)	
SC	0.1664	(0.0576)	***
ST	0.2771	(0.1194)	*
UMH	0.2796	(0.1080)	**
Muslim	0.3405	(0.0612)	***
chi2(22) for zero slope	179.28 ***		
Pseudo R2	0.1827		

Notes: (1) NOB is 748.

(2) Since this is the first-stage estimation for Table 6 and 7, child-level probit regressions were adopted with weighting to correct for the difference in sampling probability.

(3) "dF/dX" shows the marginal effect on the probability of cc=1 evaluated at sample means when the explanatory variable is continuous and it shows the discrete change in the probability when the explanatory variable is a dummy.

○

Appendix Table 3: Determinants of Mother's Remunerative Working Time

	Coeff.	Std.error	
hd_age	0.072	(0.024)	
f_edud	-0.250	(0.092)	***
m_edud	0.409	(0.176)	**
hhsize	0.064	(0.075)	
s_am	0.105	(0.036)	***
s_af	-0.019	(0.040)	
s_cm	0.202	(0.033)	***
s_cf	0.180	(0.034)	***
s_inf	0.081	(0.047)	*
acr_ir	0.012	(0.008)	*
bullock_q	0.455	(0.261)	*
bplhold	0.228	(0.612)	
hdf_lit	0.699	(0.563)	
hdm_lit	-1.260	(0.967)	
spf_lit	-0.518	(0.571)	
spm_lit	2.030	(2.295)	
hdp_adiff	0.062	(0.061)	
spp_adiff	0.057	(0.071)	
SC	-1.263	(0.560)	**
ST	3.737	(1.645)	**
UMH	-4.446	(1.045)	***
Muslim	-0.105	(0.718)	
NOB		805	
F statistics for zero slope		40.42	***
R2		0.4808	

Notes: Dependent variable is motwor. Since this is the first-stage estimation for Table 7, child-level regression with weighting to correct for the difference in sampling probability (heteroscedasticity-robust standard errors used).