Forthcoming in *The Developing Economies*

Volume: 44 (Issue: 4)

The Developing Economies, XLIV-4 (December 2006):

ON THE MOTHER AND CHILD LABOR NEXUS UNDER CREDIT CONSTRAINTS: FINDINGS FROM RURAL INDIA

YASUYUKI SAWADA,[1] KENSUKE KUBO,[2] NOBUHIKO FUWA,[3] SEIRO ITO,[2] AND TAKASHI KUROSAKI[4]

[1]*Faculty of Economics, University of Tokyo, Japan;* [2]*Institute of Developing Economies, JETRO, Chiba, Japan;* [3]*Graduate School of Science and Technology, Chiba University, Japan; and* [4]*Institute of Economic Research, Hitotsubashi University, Tokyo, Japan*

First version received March 2006; final version accepted June 2006

There is an emerging consensus that lack of credit is a major cause of child labor and inequality in the intrahousehold distribution of resources. At the same time, patterns in how children spend their time appear to be strongly influenced by maternal employment decisions. This paper includes an assessment of the effect of credit constraints on maternal employment and that of maternal employment on the intrahousehold allocation of labor, a nexus which has been left unexplored by existing studies. Three findings emerge: (1) a mother is more likely to work outside when a household lacks resources, and her domestic labor can be easily replaced by other members, (2) credit market accessibility is a major determinant of maternal labor, and (3) elder daughters assume a large part of the burden of maternal employment by providing domestic labor. Under binding credit constraints, results of this study support the collective as opposed to the unitary model of households.

Keywords: Child labor; Credit constraints; Gender discrimination; India, Intrahousehold resource allocation
JEL classification: I21, I32, J13, J16, J22, O12, O15, O16

I. INTRODUCTION

According to the U hypothesis of female labor market participation in the process of economic development (Durand 1975; Goldin 1995), participation in the female labor force tends to decline in the early stages of economic development and then subsequently increases. Along the latter part of the U curve, an increase of participation in the female labor market is in general regarded as a sign of better achievement in developed countries (Mammen and Paxson 2000). While the low labor participation rate of women is often regarded as an outcome of quantity and wage discrimination, more women generally decide to work outside as a result of better labor market conditions as the country's economic condition improves. Even within middle-income countries, there is a growing literature regarding the positive impact of childcare services on maternal employment (Hallman *et al*. 2005; Connelly, DeGraff, and Levison 1996; Lokshin, Glinskaya, and Garcia 2000).

However, in the earlier stages of economic development, when agriculture is the dominant mode of production, female labor participation in family farms, household businesses, and domestic workshops should be very high. While forms of female labor vary depending on the society, the wage labor participation rate in India is unusually high for poor families. Using Indian household data, Mammen and Paxson (2000) found that while the Indian female labor force participation rates did not exceed 60%, more than 60% of working-aged women at the lowest levels of per capita expenditure in both rural and urban areas worked for wages. In this case, the high labor participation rate of women should be understood as a response to poverty and resource constraints under limited market accessibility. Often, researchers identify the low level of female labor market participation and exclusion from formal sector jobs as a source of lower well-being or "marginalization" of women (Boserup 1970). Yet, such an interpretation may be misleading unless the constraints that households face and the consequences of maternal labor participation on labor allocation within households are considered. These often lead to an increase in child labor, especially daughters engaged in domestic work.

One reason why girls within households might fare badly is that in poor credit-constrained families, siblings must compete for resources. Boys often have the advantage, possibly because investments in boys yield higher future returns to parents than do investments in girls (Mammen and Paxson 2000; Garg and Morduch 1998). In developing countries, poor households, especially landless farm households, frequently cannot borrow against future income due to asymmetric information between lenders and borrowers (Stiglitz and Weiss 1981; Carter 1988; Pender 1996). Indeed, the lack of credit accessibility is identified as one of the most serious sources of poverty (Deaton 1997; Morduch 1994). As such, when resources are limited, households are likely to have a relatively high marginal utility of current consumption. This situation will have two grave consequences. First, the labor income for mothers from outside will generate high value for the family. Accordingly, their labor participation will increase significantly. Second, since the opportunity costs of child education are quite high relative to loss of marginal utility, the poor may choose to optimize their situation by not educating their children, even though there are high rates of return on education. In either case, a poor household gains by allowing mothers to work outside and children to work inside the household.

In this paper, we investigate the determinants of simultaneous decision-making regarding mother and child labor allocation under credit constraints. This study bridges the existing gap in two bodies of literature related to credit constraints, one involving child labor and schooling and the other regarding female labor supply. In the first body of literature, there are studies that analyze the impact of borrowing constraints on schooling and the labor supply of children in the context of developing countries (Jacoby 1994; Jacoby and Skoufias 1997; Edmonds 2004; Beegle, Dehejia, and Gatti 2003; Baland and Robinson 2000).[1] For example, Jacoby (1994) showed that constraints on borrowing have a negative influence on primary school attendance patterns in Peru. Baland and Robinson (2000) showed that there is an oversupply of child labor when a family faces credit constraints and its marginal utility of consumption is high. When there are multiple children and resource constraints are binding, elder daughters may bear a good part of that burden by providing domestic labor (Strauss and Thomas 1995, p. 1990). Having many elder sisters can increase the probability of entering school for younger brothers and sisters (Parish and Willis 1993).

The second body of literature includes empirical studies of the labor supply in developing countries. For example, studies of Indian villages have shown that labor market participation acts as informal but strong insurance against crop income fluctuations (Walker and Ryan 1990, pp. 87–88; Kochar 1999). However, assuming no market constraints, intertemporal models predict that households will choose to supply relatively more labor in periods in which wages are higher (MaCurdy 1981). On the other hand, credit market imperfections impose considerable barriers in the intertemporal allocation of the labor supply, especially that of women engaged in household domestic chores. Using panel data from India, Skoufias (1996) found that credit constraints appear to be more serious for landless and small-farm households than for large-farm households. Such credit constraints are found to limit the possibility of substituting the female labor supply over time. Accordingly, households with constrained credit are likely to supply more female labor when their resources decline.

There are also studies that investigate associations between the employment status of a mother and the probability of her child working. A mother's wage rate is an important determinant of the allocation of her children's labor. There is a large substitution effect between domestic work of children, especially girls, and that of mothers. Thus, the opportunity costs of girls' schooling are not only their own wages but also those of their mothers.[2] By using data from Bolivia, Columbia, Côte d'Ivoire, and the Philippines, Grootaert and Patrinos (1999) found that the mother's employment usually leads to an increase in child labor, usually that of female children. Despite different social and cultural characteristics in these four countries, the consistency of results is remarkable.

We extend these existing studies by integrating three important aspects: (1) the employment status of mothers, (2) child labor and schooling, and (3) credit constraints. Two hypotheses are tested formally: The first is that under credit constraints, labor participation of mothers will lead to withdrawing daughters from schools and to engaging them in domestic work. The second hypothesis is that mothers operating under binding credit constraints will be more likely to engage in work outside the home than mothers who are unconstrained. Supporting evidence for these two hypotheses is found in data from rural Andhra Pradesh, India. Under binding credit constraints, results of this paper support the collective rather than the unitary model of households.

Section II of this paper includes a description of the data used in econometric estimation; particular emphasis is placed on credit constraint and variables related to time allocation. The estimation strategy and empirical results associated with the relationship between child time allocation and maternal employment is presented in Section III. A more extensive assessment of the mechanism of maternal employment, focusing on the role of credit constraints and the determinants of those constraints, is made in Section IV. Section V includes a summary and conclusions.

II. DATA

Data used in this study came from a survey of approximately 400 rural households in the Kurnool district of the southern Indian state of Andhra Pradesh. The survey was conducted from February through April 2005 in a cluster of 32 villages. It was designed to obtain information at the household and individual level on consumption, production, assets, allocation of time, and several other economic indicators. Further details on survey design and objectives may be found in Fuwa *et al*. (2006a).

The geographical area of the survey has a high incidence of child labor by Indian standards, and there are gender disparities in school enrollment similar to what is observed in the northern states of Uttar Pradesh (UP) and Bihar.[3] The area provides a good setting for the research questions in this study due to variability in maternal employment and child time allocation patterns.

A. *Time Allocation*

The survey contained a "one week time use module" that had a reference period of seven days immediately prior to the interview date. Each respondent to the questionnaire was asked about his/her activity in each "half-day" (AM or PM) during the reference period. Thus, a total of 14 half-days were classified using 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

Maternal employment is described by the indicator variable, *ind_mw*. This was set 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 was the wife of the household head. Otherwise, the indicator was assigned a value of zero. Likewise, the employment of husbands (paternal employment) was described by the indicator variable *ind_fw*.

Child time use in each activity was measured as the number of half-days spent on that activity during the reference period. Thus, this variable took on integer values between 0 and 14.

Table 1 shows descriptive statistics for maternal employment, child time allocation, and the husband's working hours in all sample households. In terms of the number of children and child time use patterns, except for the number of infants in the household and time spent by girls at remunerative work, there was no statistically significant difference between households with maternal employment and those without maternal employment. One set of point estimates seems counterintuitive. The estimated mean time spent on "chores" for girls in households with maternal employment was lower (though not statistically significant) than that for girls in households without maternal employment. It is also somewhat surprising that time spent by husbands at remunerative work was higher in households with maternal employment than in households without maternal employment. This suggests that maternal and paternal employment may not be substitutable with each other.

Gender differences are apparent in Table 1. It is most notable that girls in households with maternal employment spend significantly more time in remunerative work than in those without maternal employment. However, such tendencies are smaller and insignificant for boys. Also, the gender gaps in schooling and leisure seem to be greater under maternal employment than under no maternal employment.

These observations are interesting, but they may mask true relationships involving maternal employment. There may be individual or household characteristics, either observable or unobservable, that affect maternal employment and child time use.

B. *Data on Credit Constraints*

The conventional empirical approach to incorporating credit constraints into an estimation model is to ignore the endogeneity of these constraints and 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). The exogenous split approach, however, has two problems. First, it is unlikely that a single variable such as income-wealth ratio or land ownership will be a good predictor of consumer ability to borrow (Garcia, Lusardi, and Ng 1997, p. 158). Second, credit constraint is endogenously generated and thus should be treated as an endogenous variable. Otherwise, estimation results will suffer from endogeneity bias (Scott 2000).

In order to overcome these problems, we designed the credit module of the questionnaire in this study carefully in order to identify credit-constrained households directly. In identifying credit constraints, we asked the head of households about the experience of household members with credit suppliers during the 12 months prior to the survey. To construct liquidity constraint indicators with sufficient variation across households, focus was placed on bank credit. This was done for the following reasons: First, clear divisions between credit constrained and unconstrained households are usually found in the context of banks or “formal” credit institutions. This is because access is often determined by the household’s ability to provide collateral, and this generally depends on ownership of land title. On the other hand, informal credit comes in numerous forms. Thus, it is difficult to classify households according to credit constraint status in the informal credit markets, and the determinants of access are less clear. Second, over the last few decades, formal sources of finance have become more accessible and important to the village economy in the study area. Studies conducted in rural Andhra Pradesh during the 1970s and 1980s by the International Crop Research Institute for the Semi-Arid Tropic (ICRISAT) note the importance of informal financial institutions, in particular the village moneylender (Walker and Ryan 1990; Pender 1996). More recently, however, Deb *et al*. (2002) found that formal sources of credit have become more accessible, and that the role of the village moneylender has diminished. The impact of increasing formal credit on household behavior is therefore interesting in itself.

We use two definitions to identify credit-constrained households; “narrow” and “broad.” Conceptually, we need to determine whether or not a household had tried to obtain a loan in a particular period. Those who had tried to borrow money were then asked whether or not they could borrow as much as requested. If the answer was yes, the household was identified as unconstrained under both definitions. Households having loan applications rejected or being unable to borrow sufficiently were identified as credit constrained in both the narrow and broad sense.

In our two definitions, we asked those who had not tried to borrow about the reasons for not trying. Answer choices were as follows:

1. No need for credit
2. Do 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 would be refused by lender
8. Do not know how to get credit or do not know lender
9. Do not know anyone who can be guarantor
10. Other

Respondents who chose any of options (3) through (9) as the reason for not attempting to obtain bank credit were identified as constrained households under the “broad definition of credit constraint.” Remaining respondents who did not try to borrow were considered to be unconstrained under this definition. However, respondents who chose any of options (3) through (5) might not be credit constrained in reality. Hence, we use a similar procedure to construct an indicator variable under the “narrow definition of credit constraint.” Households choosing any of options (6) through (9) were identified as constrained under this definition. The remaining respondents were regarded as unconstrained.

On the basis of these responses, we identify credit-constrained households that were not able to access credit. Since almost none of the existing multipurpose household panel surveys include direct questions that identify credit constraints (Scott 2000), the dataset used in this study provides valuable information to separate constrained and unconstrained households directly.

Table 2 shows the descriptive statistics for the 331 households used in this study. Among them, 205 households were identified as credit constrained, and 126 identified as unconstrained in the weak sense (using the broad definition). This indicates that a significant proportion of households were credit constrained.[4]

While age and education profiles of constrained and unconstrained households are remarkably similar, the value of land owned by credit-constrained households is significantly lower than that owned by unconstrained households. It is interesting to note that despite this contrast in landholding, there is no significant difference in average per capita consumption.

C. *Individual Child Characteristics and Demographic Variables*

In order to mitigate omitted variable bias arising from unobserved individual and household-level effects, we include individual child characteristics (including age and sex) and demographic variables. Individual characteristics of parents, such as age (*m_age* for mother's age, *f_age* for father's age) and years of education (*m_edu* for mother's education, *f_edu* for father's education) were also used.

For household-level demographic variables, the number of people residing in each household was decomposed to create household-level demographic variables as follows: *amales* (adult males 15–60 years old), *afemales* (adult females 15–60 years old), *boys* (boys 5–14 years old), *girls* (girls 5–14 years old), and *infants* (both sexes 0–4 years old). We also included counts of elderly men and women (61 years and older) in the household as *emales* and *efemales*. The number of adult members would be expected to capture shifts in demand for family labor. All else equal, a higher number of adult members lowers demand for family labor. The number of school-age children would also be expected to have a shifting effect, although the distribution of schooling among children complicates substitution patterns. The number of infants affects demand for domestic labor, especially by adult women and girls, because of the need for child care.

D. *Assets*

The variable *landval* is defined as the market value of currently owned land, measured in rupees, and *acr_ir* is defined as the acreage of irrigated land cultivated by the household. The former would be expected to capture the household's ability to present collateral for loans, while the latter might increase demand for family labor through the "productivity" effect, at the same time perhaps increasing time allocation to education and leisure through an income effect. This study's focus on irrigated land is based on the fact that it creates stronger demand for family labor than rain-fed land. The number of livestock, which is captured in the variable *bullocks* (number of bullocks), would be expected to have similar productivity and income effects.[5]

E. *Extra-household Environmental Parameters*

Literacy and age of grandparents are used as proxy variables for extra-household environmental parameters (EEPs). Whether or not these variables affect intrahousehold time allocation patterns provides a test of the validity of a collective household versus a unitary model.[6]

III. CHILD TIME ALLOCATION AND MOTHER'S WORK

When credit constraints are binding, households face a large marginal utility of consumption. In such a situation, the household has an incentive to supply a larger amount of labor so that consumption can be smoothed with the additional income. Using the ICRISAT panel data from Andhra Pradesh in India, Kochar (1999) found that adult males in the household increase their market hours of work in response to unanticipated negative shocks to crop profits. This finding suggests that adult male labor may be modeled as a function of credit constraints in addition to household and/or member characteristics. If it is assumed that there is a "pecking order" of labor supply from the husband's labor to the wife's labor against an unanticipated income shock, then the wife's labor supply will be a function of the husband's labor supply as well as credit constraints and other characteristics. This sequential decision pattern may be seen as a peculiar one. Theoretically speaking, it will be more natural to assume that paternal and maternal labor decisions are determined simultaneously.[7] However, in the context of rural South Indian society, we believe that the pecking order of labor supply from husband's labor to the wife's labor will be a plausible approximation to the observed sequential labor decisions.

Once both parents enter the labor market, the opportunity cost of child schooling will become high. As a result, domestic child labor is likely to be induced. Whether this effect will be higher for daughters or for sons is an important empirical question investigated in this paper.

In this section, we focus on the relationship between the employment decision of an adult woman, or "maternal employment," and child time use. Analysis of the key issue of credit constraints can be found in Section IV.

If the framework discussed above is valid, the employment decision of a husband is exogenous to his wife's employment. To test this supposition, we employed a bivariate probit regression with husband's employment and wife's employment as a pair of dichotomous variables. Here, the husband's employment enters into the equation for the wife's employment. If the correlation between the residuals is not significantly different from zero, then we cannot reject the null hypothesis that the husband's employment is exogeneous to the determination of the wife's employment. Table 3 shows that the error-term correlation parameter ρ is not different from zero at any conventional level of statistical significance. Accordingly, the husband's labor supply may be used as an exogenous variable in the wife's employment equation.[8]

With this information, a "child time demand function" (or "child time use equation") for each activity can be derived from a household utility maximization model as follows:

$$l_{ij} = A_i\delta_j + \alpha_{ij}M + X\beta_{ij} + v_{ij} \quad (1)$$

$$M = X_M\beta_M + u \quad (2)$$

where i denotes child type (as defined over sex and/or age group) and j denotes activity. A child's time allocation for each activity is denoted by l; A is a vector of member-specific exogenous variables, M is the endogenous maternal employment, and X and X_M are vectors of household specific exogenous variables. X_M includes employment of the mother's husband, i.e., "paternal employment," and this can be taken to be an exogenous variable. While the activities of all household members affect child i's time allocation, the impact of maternal employment on children's time allocation to various activities is of primary interest in this study. Therefore, maternal employment is allowed to appear as an argument in (1) and may be determined endogenously through equation (2). Equation (1) is considered to be in reduced form with respect to the time allocations of other members so that only their exogenous determinants enter as arguments. Note that the parameter vectors α_{ij} and β_{ij} in (1) are allowed to depend on child type. This reflects differences in the impact of maternal employment and household characteristics across sex and age groups.

Estimating equation (1) involves several issues: first, maternal employment is endogenous and may be correlated with unobserved variables (such as household preference) that are embodied in the error term of the child time use equation. Second, since the sample of children includes siblings belonging to same households, it is desirable to control for household-specific effects such as the unobserved preference for education.

In order to address these issues, we used the method proposed by Pitt and Rosenzweig (1990) in the context of child time allocation and endogenous infant health. Rather than estimate equation (1) directly for each child, differences between two children from the same household were assessed.

This method has the following advantages: First, taking differences between children justifies the use of certain instrument variables for maternal employment.[9] For example, while irrigated acreage affects maternal employment, it may also affect child time use. However, if irrigated acreage is assumed to enter into the time use equations of different child types in an identical manner, then taking differences cancels out the term containing the irrigated acreage variable. This follows since there is little difference between young girls and boys in terms of the work assignments in the field. Thus irrigated acreage becomes a candidate instrument variable for maternal employment. Second, differencing allows the removal of any household-specific (common) fixed effects that enter into the time use equations, provided that their magnitudes are identical between boys and girls.

To further clarify these advantages, suppose that for a given activity, children of types i and k have the following time use equations:

$$l_i = A_i\delta + \alpha_i M + X_1\beta_{1i} + X_2\beta_2 + v_i \quad (3)$$

$$l_k = A_k\delta + \alpha_k M + X_1\beta_{1k} + X_2\beta_2 + v_k \quad (4)$$

where X_1 is a subset of the exogenous regressors with coefficients that vary across child types. X_2 contains variables that are assumed to have the same coefficients for both child types. Subtracting (4) from (3) yields:

$$l_i - l_k = (A_i - A_k)\delta + (\alpha_i - \alpha_k)M + X_1(\beta_{1i} - \beta_{1k}) + \eta_{ik} \quad (5)$$

which no longer contains the regressors in X_2 and $\eta_{ik} \equiv v_i - v_k$ where (common) household fixed effects are effectively removed. If X_2 forms part of X_M, the exogenous regressors in the maternal employment equation (2), then the variables therein can be used as instrument variables. It is of particular interest to estimate the parameters α_i–α_k, which measure the difference between child types in the effect of maternal employment *M* on time allocation *l*.

Suppose that the maternal employment variable takes a dichotomous form, defined by a dummy variable *m*. This variable takes a value of one if a mother participates in remunerative employment and zero otherwise. The time use difference equation (5), together with maternal employment equation (2), comprises an estimable econometric model as follows:

$$l_i - l_k = (A_i - A_k)\delta + (\alpha_i - \alpha_k)m + X_1(\beta_{1i} - \beta_{1k}) + \eta_{ik} \quad (5)$$

$$M = X_M \beta_M + u \quad (2)$$

$$m = \begin{cases} 1 & if\, M \geq 0 \\ 0 & if\, M < 0 \end{cases} \quad (6)$$

Further, we assume that errors follow a joint normal distribution with zero means and the following covariance matrix:

$$\begin{pmatrix} \eta \\ u \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \sigma_{\eta u} \\ \sigma_{\eta u} & 1 \end{pmatrix}\right] \quad (7)$$

where σ_u^2=1 is assumed for parameter identification.

A type 5 Tobit model with observed regime can be used to estimate the model (Amemiya 1995, pp. 399–408). The type 5 Tobit model effectively solves the endogenous sample selection bias arising in OLS estimation of equation (5). We estimate the type 5 Tobit model of equations (2), (5), and (6) by using Heckman and Lee's two-step procedure (Maddala 1983, pp. 120–21). In the first step, because only the discrete variable of *m* is observed, equations (2) and (6) are estimated as a probit model. By using the estimated coefficients of the first step, consistent estimates of adjustment terms for the conditional expectations of error terms of equation (5) can be obtained.

A. *Specification for Girl-Boy Pair Subsample*

The system of equations including (2), (5), and (6) was first estimated on the subsample containing only girl-boy child pairs, focusing on the impact of maternal employment in the following activities: household chores, schooling, childcare, leisure, and remunerated work. In order to create the differenced dependent variable as in equation (5), we generate all possible girl-boy pairs within each household. Pairs were then sorted so that the differences are taken in a specific order, "girl minus boy."

The first-stage probit equation was estimated with the following household characteristics as explanatory variables: *m_age, amales, afemales, boys, girls, infants, landval, acr_ir, m_edu,* and *ind_fw*. Here, the maternal employment equation was taken to be in reduced form with respect to the endogenous credit constraint.

In the second-stage estimation, the parameter on maternal employment was allowed to vary by sex, so that the coefficient on maternal employment, *ind_mw*, measures the difference between the coefficient for girls and the coefficient for boys. According to the ordering rule, a positive coefficient on *ind_mw* can be interpreted such that the girls' parameter on maternal employment is greater than that of the boys.

In this specification, the only individual child characteristic that was included in the time use difference equation (5) was *d_age* (difference in age within child pair). Difference in sex enters only through differences in the coefficients. Other than maternal employment, we assume that only the household level variable of *infants* was not canceled out in differencing. This assumption is justified in the literature by the observation that infants requiring childcare tend to affect the time use pattern of girls more than boys (Pitt and Rosenzweig 1990).

In all regressions in this and Section IV, sampling weights were computed following the variable probability sampling strategy. This is described in Fuwa *et al*. (2006a).

B. *Results for Girl-Boy Subsample*

Table 4 includes results from the girl-boy pair subsample. The first stage probit estimates show that an increase in the number of adult males reduces the probability of maternal employment, while an increase in the number of children (both girls and boys) increases that probability. The significant negative effect of *infants* on maternal employment can be understood relative to the increased demand for childcare that competes with remunerated work time. Irrigated acreage increases maternal employment, and this is consistent with the increased demand for family labor on the farm. A mother's years of education has a significantly negative impact on the probability that she will take up remunerative work. This may imply either relaxation of credit constraints or simply unobserved preferences. This is addressed further in Section IV. Employment of husbands increases the probability of maternal employment, and this suggests a complementarity between male and female adult labor.

Second stage linear regressions indicate significant differences between girls and boys in terms of the impact of maternal labor on time allocation. The first column shows that maternal employment significantly increases the difference between girls and boys in terms of the amount of time spent on household chores. Specifically, girls spend more time on chores relative to boys when their mother takes up employment. In the same column, the coefficient on *d_age* (which can be interpreted as the direct effect of age on time for chores according to equation (5)) is significantly positive; older children spend more time on chores than do younger. Also notable in column (1) is the significant negative coefficient of the selection term, *h*. This implies that the covariance between the errors in the first and second stage equations is significantly negative (Maddala 1983). This finding supports the assumed endogeneity of the maternal employment variable. This might happen if there were an omitted variable that exerted an upward impact on women's employment but a negative impact on girls' chores relative to those of boys. Specification of such omitted variables may be difficult, but one candidate is the mother's innate ability, which could improve her prospects in the labor market as well as reduce the demand for time daughters spend on household chores.

The result related to schooling in column (2) is consistent with what we found for household chores. The negative impact of maternal employment on girls' time for schooling is larger (more negative) than on that of boys. This implies that girls shorten their schooling more than boys in response to their mother working outside the home, partly in order to spend more time on household chores. The coefficient on *d_age* is significantly negative, and this implies that the girl-boy schooling gap grows with age differences between the two children. This in turn implies that older girls spend less time at school. According to the estimated coefficient of the selection correction term, *h*, the error term in the schooling equation has significant positive covariance with the probit error term. Again, this appears to suggest the mother's innate ability as an omitted variable.

The childcare equation in column (3) shows that having infants in the same household significantly increases the difference between girls and boys in the time spent on childcare. This is quite intuitive and straightforward. In the following column, leisure appears to follow a similar pattern as schooling. Maternal employment negatively affects the difference "girl leisure time minus boy leisure time." With this difference being negative to begin with, maternal employment only makes the difference worse. The remunerative work equation in column (5) shows a significant positive coefficient on *d_age*. This supports the common observation that older children are more likely to be employed in remunerative work than are younger.

C. *Specification for Full Sample*

In order to incorporate information from same-sex child pairs, the system defined by equations (2), (5), and (6) was estimated on the full sample of child pairs. Here, the parameter on the maternal employment indicator was allowed to vary by relative birth order within pairs as well as by sex. If the parameter varied only by sex, then *ind_mw* would be canceled out in same-sex child pairs, and this would defeat the purpose of pooling observations.

In constructing the differenced dependent variable, all possible pairs of children within each household were generated. Pairs were sorted so that differences could be assessed according to the following general rules: "girl minus boy" and "older child minus younger child." When there was a conflict between sex and age ordering, sex was given priority. In this way, a girl-boy pair, where the girl was younger than the boy, would be differenced according to the "girl minus boy" rule.

As with the girl-boy subsample, *age* was included as an individual characteristic, and *infants* as the household specific exogenous variable that was not cancelled out in the differencing. Covariates in the first-stage probit are the same as in the girl-boy subsample.

In order to allow the coefficient on *ind_mw* and *infants* to vary across child types, the Heckman and Lee two-step procedure for endogenous dummy variables described by Maddala (1983, pp. 120–21) was followed. Interaction variables were used to capture the differential effect of the explanatory variables, *ind_mw* and *infants*. For example, the interaction term *ind_mw*girl_boy*old_young* picks up the difference in the maternal employment parameter between a girl and her younger brother.

D. Results for Full Sample

Table 5 shows results for the full sample. All the variables that were significant in the probit model of Table 4 (except for *m_edu)* were significant and of the same sign.

In the time use equations, column (1) shows that the impact of maternal employment on girls' chores is higher than that on boys' chores, even when the girls are younger. In fact, comparison of the coefficient estimates on *d_age* and *ind_mw*girl_boy*young_old* suggests that a girl has to be approximately fourteen years younger than a boy in order for both children to receive a similar impact from maternal employment on their time for chores.

The schooling equation in column (2) shows that the negative impact of maternal employment on girls' schooling, relative to boys, is greater when the girl is older than the boy (compare the coefficients on *ind_mw*girl_boy*old_young* and *ind_mw*girl_boy*young_old* in column (2)). On the other hand, column (3) shows that the difference relative to the effect of infants on time spent on childcare is highest between girl-boy pairs in cases where the girl is younger. In response to an additional infant, younger girls spend more time on childcare relative to their brothers. Column (2) describes this phenomenon from another angle: In response to an additional infant, younger girls reduce their schooling hours more than older girls, relative to boys. This is seen from the significant negative coefficient on *infants*girl_boy*young_old* in column (2).

Column (4) indicates that younger girls are cutting back their leisure (relative to older boys) in response to maternal employment. This stands in interesting contrast to the finding in column (2), where in response to their mother's employment, older girls are seen to cut back larger chunks of their schooling than are younger girls. Finally, age appears to have a positive impact on remunerative work. However, the impact of maternal labor or infants on remunerative work is not as clear as in the case of other activities.

IV. MOTHER'S WORK AND CREDIT CONSTRAINTS

Imperfect information in credit markets often generates credit rationing on the poor. In poor credit-constrained households, the marginal utility of current consumption is likely to be higher than that in unconstrained households. Further, such credit constraints impose strong barriers in the intertemporal allocation of the female labor supply (Skoufias 1996). Accordingly, in India, a significant proportion of women at the lowest income levels work for wages because they are more likely to be credit constrained (Mammen and Paxson 2000).

In order to set up an empirical model for maternal labor participation and examine the validity of the effect of credit constraints, the following linear equation is postulated:

$$M = \alpha_c cc + X_M \beta_M + \eta F + u \quad , \qquad (8)$$

where, as before, M is mother's time allocated to remunerative work during the reference period. Unlike equation (2), equation (8) includes an additional variable, *cc*, which is an indicator of credit constraints. It takes the value of one if the credit constraint is binding and zero otherwise. X_M is a matrix of household characteristics such as member age and years of schooling, the household's human and physical assets, and other control variables. F is the husband's time allocated to remunerative work during the reference period. The last term on the right hand side, u, denotes a well-behaved error term. Since maternal labor participation, M, is not perfectly unobservable from the data set, it is treated as a latent variable, and a binary dependent variable model is employed to estimate equation (8).

A. *Endogenous Credit Constraints and Paternal Labor*

Following Jappelli (1990), in order to consider multiple endogenous determinants of credit constraints, a qualitative response model of endogenous credit constraint is constructed by defining an indicator variable of credit constraint, *cc*. Let C^* represent the optimal consumption in the absence of a current credit constraint. $C^* = C$, actual consumption, if the credit constraint is not binding; $C^* > C$ if the credit constraint is binding. Define the gap between C and C^*, i.e., $H^* = C - C^*$. Here, two factors are considered to determine whether or not H^* takes a negative value, i.e., whether or not the constraint is binding (Jappelli 1990). The first factor is the demand for credit, and this is represented by the difference between consumption and the individual's own resources. The second factor includes how many financial intermediaries are willing to supply credit to this individual. Further, following Hayashi (1985) and Jappelli (1990), it is assumed that the reduced form of optimal consumption C^* can be expressed as a linear function of observables such as the household's human and physical assets. The maximum amount of borrowing is also assumed to be a linear function of the same variables. Then, consider the following equation, in reduced form, of the consumption gap variable:

$$H^* = Z\pi + \varepsilon \quad , \qquad (9)$$

where Z includes the household head's age, household demographic and asset variables, and ε is an error term which captures unobserved elements and measurement errors. If $H^* < 0$, the credit constraint is binding, and $cc = 1$. If $H^* \geq 0$, the credit constraint is not binding, and therefore $cc = 0$.

The econometric model in this study is composed of three interrelated binary dependent variable models. The first model for maternal labor participation is composed of the binary response model of equations (8) and (10):

$$M = \alpha_c cc + X_M \beta_M + \eta F + u \quad (8)$$

$$m = \begin{cases} 1 & if\, M \geq 0 \\ 0 & if\, M < 0 \end{cases} \quad (10)$$

The second equation for credit constraint consists of equations (9) and (11):

$$H^* = Z\pi + \varepsilon \quad (9)$$

$$cc = \begin{cases} 1 & if\, H^* < 0 \\ 0 & if\, H^* \geq 0 \end{cases} \quad (11)$$

Paternal employment can also be expressed with the following latent equation and discrete dependent variable model:

$$F = \gamma cc + X_F \beta_F + \xi \quad (12)$$

$$f = \begin{cases} 1 & if\, F \geq 0 \\ 0 & if\, F < 0 \end{cases} \quad (13)$$

where f represents whether or not the father participates in the labor market. Finally, after replacing the latent variable F by an observable dichotomous variable f in equation (8), equations (8), (9), (10), (11), (12), and (13) comprises a three-equation trivariate probit model under the assumption of joint normality of the mean-zero error terms u, ε, and ξ. The conditions var(u) = var(ε) = var(ξ) = 1 must be imposed for identification. The variance-covariance matrix of u, ε, and ξ is symmetric, and the covariances are allowed to be non-zero.

In order to estimate the parameters under this setting, a log-likelihood function can be used, and this is derived from the trivariate standard normal distribution function. We use the algorithm given in Cappellari and Jenkins (2003) in order to estimate the trivariate probit model using the method of simulated maximum likelihood also known as the Geweke-Hajivassiliou-Keane (GHK) estimator.

From Section III, paternal employment can safely be considered as an exogenous variable in the maternal employment equation. However, it is useful to substitute F in equation (8) with equation (12) from which the following expression, in reduced form, is obtained:

$$M = (\alpha_c + \eta\gamma)cc + X_{MF}\beta_{MF} + \omega \quad (8)'$$

where $X_{MF} \equiv [X_M \; X_F]$ and $\omega = u + \eta\zeta$. Using (8)', the trivariate model can be reduced to a bivariate probit model which is composed of equations (8)', (9), (10), and (11).

If the unobserved component of the credit constrained variable, ε, is systematically correlated with unobserved characteristics, ω, which influence maternal labor, there will be an endogeneity problem of credit constraints. In this case, repeated estimation of the single binary dependent variable model is not appropriate. In order to estimate parameters of this model where cov(ε,ω) = $\rho \neq 0$, we employ the full information maximum likelihood (FIML) method.[10] In the system of equations including (8)', (9), (10), and (11), the conditions var(ε) = 1 and var(ω) = 1 must be imposed for identification. Further, in order to identify parameters, the variables Z in equation (9) must contain at least one instrumental variable that is not in the maternal labor equation (8)'. Land value is used as a reasonable choice for the identifying instrumental variable; the value of land will affect credit availability directly while maternal labor participation will be affected by operating land size, rather than its value. This is justified by the fact that labor demand is proportional to land size but not necessarily to land value due to the natural limit in labor use for a given piece of land irrespective of land productivity. Land value will be determined largely by capital and material inputs.

B. *Estimation Results*

Tables 6-1 and 6-2 present results of the bivariate probit model in reduced form based on (8)', (9), (10), and (11) with broadly and narrowly defined credit constraints, respectively. Tables 7-1 and 7-2 show results of the trivariate model in structural form based on equations (8), (9), (10), (11), (12), and (13). The estimate of each model is based on different specifications in order to check the robustness of the results.

1. *Maternal employment equation*

The probit results with the broadly defined credit constraint in Table 6-1 indicate that the credit constraint variable has a positive coefficient in the maternal labor supply equation. However, the coefficients are statistically insignificant in all specifications. Although the signs are opposite, the ages of both fathers and mothers have significant coefficients in columns (1) and (2). Younger mothers are more likely to be employed, as are mothers with older husbands.

With narrowly defined credit constraints, the coefficients on credit constraints in the maternal labor supply equations become positive and statistically significant in most specifications (Table 6-2). This result indicates that facing credit constraints, mothers have systematically higher probabilities of participating in the labor market. The sign of this coefficient is consistent across different specifications, suggesting robustness of the model.

Columns (2) and (4) of Tables 6-1 and 6-2 include variables describing the parents of the head of the household and spouse. These variables are regarded as proxies for extra-household environmental parameters (EEPs) and thus influence bargaining powers of individuals. In column (4), the dummy variable representing literacy of the mother of the household head, *hdm_lit*, has a significant negative coefficient. This could reflect unobserved wealth or preferences, or it may suggest rejection of the unitary model of the household (Ito 2006; Fuwa *et al*. 2006b). For example, if the mother of the head of household is literate, this may strengthen the bargaining power of female members in general. This effect may then spill over into the employment decisions of working aged women. However, this result should be viewed cautiously because there are only eight households in the study sample where the mother of the head of household is literate.

In order to mitigate the omitted variable bias arising from unobserved heterogeneity, caste dummies (*backward caste*, *scheduled caste*, *upper/medium Hindu caste*, *scheduled tribe*, and *Muslim*) were included in specifications (3) and (4) of Tables 6-1 and 6-2.[11] While the basic qualitative results are maintained, the scheduled tribe dummy variable has a negative and statistically significant impact on labor participation by mothers. This suggests that there may be a cultural aversion to female employment outside the home, or possibly that there may be a lack of employment opportunities. The correlation coefficient of disturbances for columns in Table 6-1 is consistently positive, but it is negative in Table 6-2. Neither is statistically significant; Wald tests indicate that the null hypothesis of zero correlation cannot be rejected.

2. *Credit constraint equation*

Table 6-1 shows that estimated coefficients in the credit constraint equations are consistent with theoretical predictions (such as the negative coefficient on *landval*). However, most of the coefficients are statistically insignificant. Moreover, the independent variables are highly correlated with each other. For example, the correlation coefficient of *landval* and its square is 0.9. The variable *hhsize* and its subset *amales*, *afemales*, *emales*, and *efemales* are highly correlated. This implies a multicolinearity problem. In fact, if we use *landval* and *hhsize* only as independent variables, then the coefficient for the former and the latter are positive and negative, respectively, and they are statistically significant. Yet, we decided to include as many variables as possible in order to mitigate problems arising from omitted variables, weak instruments, and weak identification.

Columns (3) and (4) of Table 6-1 demonstrate that the *Muslim* dummy has a positive and significant coefficient. This suggests that Muslims may face systematically higher probabilities of credit constraints than other groups. As seen in Table 6-2, when employing the narrow definition of credit constrained-ness, the variable of male elderly members (*emales*) reaches statistical significance. This coefficient is negative and suggests that higher human capital may significantly relax credit constraints. It may also suggest that households where elderly members reside are more likely to receive bequests.

3. *Trivariate probit model*

The structural mechanism through which credit constraints increase maternal employment was examined using results from the trivariate probit model presented in Tables 7-1 and 7-2. This would expand on the finding that credit constraints influence employment status of mothers.

From both tables, it is clear that credit constraints affect paternal employment in a positive manner. In seven out of eight columns, the positive coefficient on the credit constraint variable (*b_cc* or *b_cc2)* in the paternal employment equation (middle panel) is statistically significant. This suggests that credit constraints make fathers to work more.

Mixed results regarding the effect of credit constraints on maternal employment were obtained. In columns (2) and (3) of Table 7-1 and column (3) of Table 7-2, the coefficient on the credit constraint variable is negative and statistically significant. On the other hand, the same coefficient is positive and significant in columns (2) and (4) of Table 7-2. The employment status of husbands seems to clearly have a positive impact on maternal employment. The coefficient on *ind_fw* is positive and statistically significant in columns (2) and (3) of Table 7-1, and column (3) of Table 7-2, and this supports observations in Section III. Thus, there is likely to be a complementary relationship between paternal employment and maternal employment.

These findings suggest that the lack of access to credit or the inability to borrow causes husbands to work more. Such credit constraint has an ambiguous effect on maternal employment per se but an indirect effect in that an increase in paternal employment may increase maternal employment.

Other results found in Tables 7-1 and 7-2 are in general consistent with those found using the bivariate probit model: Literacy of the mother of the household head (*hdm_lit*) has a negative effect on maternal employment (columns (2) and (4)). Households belonging to scheduled tribes are less likely to have working mothers (column (4)). Muslim households are more likely to be credit constrained (columns (3) and (4) of Table 7-1, lower panel). The existence of elderly males (*emales*) tends to relax credit constraints (columns (2) and (4) of Table 7-2, lower panel). Mothers in upper/medium Hindu caste households appear to have a higher propensity for employment (column (3)). However, those same households may be more likely to be credit constrained (columns (3) and (4) of Table 7-2).

Additional findings come from the paternal equation model. The positive and significant coefficients on *boys* and *bullocks* in the paternal employment equation suggest a complementary relationship among labor inputs. On the other hand, the positive effect of the number of boys may mean that husbands work harder to pay for the education of their sons. It also appears that husbands work less if there are more adult females (*afemales*) in the household.

V. CONCLUSIONS

This paper included an assessment of the effects of maternal labor on intrahousehold inequality of time allocation and those of credit constraints on maternal labor within a unified framework. Analysis led to three significant findings:

First, mothers' labor participation seems to generate an undesirable negative impact on intrahousehold labor resource allocation. Elder daughters may bear a major part of the burden of maternal labor participation by terminating their education to provide domestic labor.

Second, credit market accessibility is identified as a major factor leading to maternal employment by constraining the household's resource availability. Thus, credit constraints have an indirect effect on the time allocation of children through the mother's employment decision.

Finally, the direct impact of credit constraint on maternal employment is ambiguous. It is mainly through an indirect effect involving paternal employment that credit constraints affect maternal employment. Credit constraints compel fathers to work more, and this in turn increases the probability of employment for wives. This is due to a complementary relationship between the employment status of both husbands and wives.

A proxy variable for extra-household environmental parameters (EEPs) was found to have a significant coefficient when we estimate maternal employment equations. This finding suggests that a unitary model of the household may be rejected while collective models of the household are supported.

We investigated the determinants of simultaneous decision making of mother and child labor allocation under credit constraints. This study thus bridges the existing gap between two separate bodies of literature: one on child labor and schooling, and the other on female labor supply, both under credit constraints. It should be noted, however, that the study may be somewhat limited by the size of the data set used. Thus, while new ground has been broken, it is important that these findings be examined with larger panel data sets in the future.

FOOTNOTES

[1] Rosenzweig and Evenson (1977) constructed and empirically implemented a static neoclassical household model that explicitly takes into account the economic contribution of children in agricultural areas. Findings using data from India support the hypothesis that one of the basic conditions that motivated Indian families to bear relatively large numbers of

children in the late 1950s was the high return on the use of the raw labor power of children compared to investment in skills children could obtain from schools.

[2] Strictly speaking, a mother's wage creates income effects for the family, so higher wages for mothers might reduce the child labor supply.

[3] See Kurosaki *et al*. (2006). As further noted by these authors, a higher incidence of girls' labor in remunerative jobs relative to UP and Bihar, was also observed.

[4] If the narrow definition is used, 164 households are identified as credit constrained and 167 as unconstrained.

[5] Kurosaki *et al*. (2006) discusses the impact of asset holdings on child labor in more detail.

[6] See Fuwa *et al*. (2006b) for further discussion.

[7] Fuwa *et al*. (2006c) elaborate on the formal modeling of sequential labor decisions.

[8] As an alternative, we used the method suggested by Datt and Ravallion (1994). In this method, the residuals generated from a Tobit model of the husband's employment are used as explanatory variables in a Probit model for wife's employment. The null hypothesis that the husband's employment is exogenous cannot be rejected if, in the wife's employment equation, the coefficient on the generated residuals term is not significantly different from zero. In this study, the estimate for the coefficient on the residual term yielded a *t*-value of –1.37, which does not allow rejection of the null hypothesis.

[9] See Pitt and Rosenzweig (1990, pp. 974–75).

[10] It is easy to verify that when the covariance is zero, the model can be estimated as consecutive single probits.

[11] The *backward caste* dummy variable was omitted in the estimation to avoid collinearity with the constant term in the credit constraint equation. When we included a constant term in the maternal employment equation, however, the estimated correlation coefficient, ρ, converged to either 1 or – 1, which is implausible. Accordingly, we suspect a collinearity problem among the explanatory variables. In order to obtain reasonable estimates (and to achieve proper identification), we have decided to omit the constant term from the estimation of the maternal employment equation.

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TABLE 1

Relationship between Maternal Employment and Child Time Allocation

	No Maternal Employment (1)	Maternal Employment (2)	Mother Not in Household (3)	p-value of H_0: Col. (1) Minus Col. (2) = 0 (4)
No. of mothers	150	237	29	–
Avg. no. of school-age daughters†	1.227	1.228	0.759	0.991
	(0.977)	(1.053)	(0.786)	
Avg. no. of school-age sons†	1.260	1.257	1.000	0.977
	(0.839)	(0.896)	(0.964)	
Avg. no. of infants	0.667	0.477	–	0.043
	(0.953)	(0.861)		
Schooling (avg. no. of half-days per child):				
Girls	3.709	3.298	2.824	0.429
	(4.569)	(4.094)	(4.202)	
Boys	4.099	4.731	3.967	0.259
	(4.927)	(4.806)	(4.510)	
Chores (avg. no. of half-days per child):				
Girls	1.742	1.544	1.235	0.599
	(3.256)	(2.998)	(2.751)	
Boys	0.343	0.177	0.000	0.167
	(1.197)	(0.935)	(0.000)	
Child care (avg. no. of half-days per child):				
Girls	0.515	0.640	0.088	0.661
	(2.013)	(2.521)	(0.364)	
Boys	0.074	0.121	0.000	0.594
	(0.656)	(0.837)	(0.000)	
Remunerative work (avg. no. of half-days per child):				
Girls	2.020	3.990	5.147	0.001
	(0.398)	(0.382)	(6.025)	
Boys	2.955	3.245	2.317	0.608
	(0.430)	(0.362)	(4.179)	
Leisure (avg. no of half-days per child):				
Girls	3.239	2.751	2.176	0.287
	(4.041)	(3.589)	(2.531)	
Boys	3.497	3.778	4.117	0.54
	(3.881)	(4.038)	(4.116)	
Remunerative work by father (avg. no. of half-days)	5.101	7.430	6.667	0.000
	(5.541)	(5.379)	(6.154)	

Note: Values in parentheses are standard errors.
† School-age includes ages 5 to 14, regardless of whether or not the child is going to school.

TABLE 2

Sample Statistics on Credit Constraints (Using Broad Definition of Credit Constrained-ness)

Variable	Unconstrained (1) Mean (Std. Dev.)	Constrained (2) Mean (Std. Dev.)	H_0: Equality of Means (3) *t* statistic (*p*-value)
Age of the head of household	44.54	44.37	0.1374
	(11.22)	(10.64)	(0.8908)
Years of schooling of the head of	1.71	1.75	– 0.111
household	(3.15)	(3.20)	(0.9117)
Years of schooling of the spouse	0.62	0.59	0.1351
of the head of household	(1.81)	(1.92)	(0.8926)
Value of owned land	1.43	0.79	1.8461
(100,000 rupees)	(4.62)	(1.40)	(0.0658)
Per capita consumption	142.4	140.1	0.1341
(rupees per week)	(117.3)	(167.0)	(0.8934)
No. of observations	126	205	

TABLE 3

Testing for Exogeneity of Paternal Employment in the Maternal Employment Decision

A. Paternal Labor Participation Equation (Dependent Variable: *ind_fw*)

	Coef.	Robust Std. Error
f_age	– 0.0013	0.0125
amales	0.1901**	0.0773
afemales	– 0.0386	0.0902
boys	0.0751	0.1076
girls	– 0.1813**	0.0921
landval	0.0159	0.0257
acr_ir	– 0.0059	0.0230
f_edu	0.0161	0.0268
bullocks	0.0749	0.1165
Constant	0.5989	0.7979

B. Maternal Labor Participation Equation (Dependent Variable: *ind_mw*)

	Coef.	Robust Std. Error
m_age	0.0110	0.0146
amales	– 0.1396	0.1287
afemales	– 0.0649	0.0773
boys	0.2490***	0.0504
girls	0.1938	0.1342
infants	– 0.1270	0.0923
landval	0.0724	0.0456
acr_ir	0.0177	0.0249
m_edu	0.0220	0.0618
ind_fw	– 0.9191	0.5709
ρ	0.9284†	0.2786
No. of observations	696	

† Wald test of $\rho = 0$: Chi2(1) = 0.66596, *p*-value = 0.4145. *** and ** represent statistical significance at the 1% and 5% level, respectively.

TABLE 4

Effect of Maternal Employment on Child Time Use (Type 5 Tobit Model Using the Girl-Boy Pair Subsample)

A. First-Stage Probit (Dependent Variable: *ind_mw*)

	Coef.	Robust Std. Error
m_age	– 0.0062	0.0088
amales	– 0.2223***	0.0729
afemales	0.0220	0.0852
boys	0.1848**	0.0832
girls	0.2545***	0.0727
infants	– 0.1857**	0.0947
landval	– 0.0072	0.0155
acr_ir	0.0525**	0.0228
m_edu	– 0.0949**	0.0395
ind_fw	0.5091***	0.1458
Constant	– 0.2486	0.3576

B. Second-Stage Linear Regression

	Dependent Variable				
	d_chores	*d_schooling*	*d_childcare*	*d_leisure*	*d_remun_work*
	(1)	(2)	(3)	(4)	(5)
d_age	0.2151 ***	– 0.5335 ***	– 0.1040**	– 0.5610***	0.8960***
	(0.0575)	(0.0840)	(0.0466)	(0.0891)	(0.1046)
infants	– 0.2116	– 0.1646	0.7650***	0.1114	– 0.3960
	(0.2227)	(0.2913)	(0.2738)	(0.3098)	(0.3858)
ind_mw	3.1674 ***	– 2.1651 ***	0.1402	– 2.1898***	0.6070
	(0.5033)	(0.4915)	(0.1655)	(0.5454)	(0.6690)
h†	– 2.4095***	1.8031***	– 0.0901	1.3872**	0.4335
	(0.4739)	(0.4519)	(0.2001)	(0.5618)	(0.6382)
No. of obs.	396	396	396	396	396

Note: Values in parentheses are robust standard errors.

† *h* is an augmenting term suggested by Maddala (1993, p. 121). It takes the form: $\phi\left(X_M\hat{\beta}\right)/\Phi\left(X_M\hat{\beta}\right)$ if *ind_mw* = 1;

$-\phi\left(X_M\hat{\beta}\right)/\left[1-\Phi\left(X_M\hat{\beta}\right)\right]$ if *ind_mw* = 0.

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

TABLE 5

Effect of Maternal Employment on Child Time Use (Type 5 Tobit Model Using the Full Sample)

A. First-Stage Probit (Dependent Variable: *ind_mw*)

	Coef.	Robust Std. Error
m_age	– 0.0052	(0.0072)
amales	– 0.2477***	(0.0565)
afemales	0.0525	(0.0710)
boys	0.1933***	(0.0506)
girls	0.2779***	(0.0456)
infants	– 0.2173***	(0.0691)
landval	0.0024	(0.0158)
acr_ir	0.0320*	(0.0168)
m_edu	– 0.0413	(0.0366)
ind_fw	0.4940 ***	(0.1096)
Constant	– 0.3106	(0.2839)
Pseudo R^2	0.1042	

B. Second-Stage Linear Regression

	Dependent Variable				
	d_chores	*d_schooling*	*d_childcare*	*d_leisure*	*d_remun_work*
	(1)	(2)	(3)	(4)	(5)
d_age	0.2221***	– 0.5364***	– 0.0671	– 0.7432***	0.8559***
	(0.0796)	(0.1045)	(0.0640)	(0.1245)	(0.1407)
*infants*girl_girl*	– 0.0341	0.6224	0.3521	– 1.4149***	0.1900
**old_young*	(0.0701)	(0.4186)	(0.3475)	(0.4605)	(0.5256)
*infants*girl_boy*	– 0.2910	0.4900	0.2514	– 0.1778	– 0.2308
**old_young*	(0.2167)	(0.3216)	(0.2396)	(0.2976)	(0.5056)
*infants*girl_boy*	– 0.0428	– 1.1335***	1.4603***	0.6079	– 0.6799
**young_old*	(0.3812)	(0.2886)	(0.5257)	(0.5381)	(0.5818)
*infants*boy_boy*	0.2154	– 0.2695	– 0.1537	– 0.2320	0.3900
**old_young*	(0.4248)	(0.2820)	(0.6202)	(0.4618)	(0.3839)
*ind_mw*girl_girl*	– 0.9808**	0.6155	0.1206	1.0854	– 0.7486
**old_young*	(0.4514)	(0.8542)	(0.4285)	(1.2456)	(1.3374)
*ind_mw*girl_boy*	3.1131***	– 2.6483***	0.4516	– 0.8865	1.0351
**old_young*	(0.7450)	(0.8520)	(0.3458)	(0.8241)	(1.0890)
*ind_mw*girl_boy*	3.1572***	– 1.4562**	– 0.2459	– 3.6640***	0.3183
**young_old*	(0.8396)	(0.7193)	(0.3613)	(1.0371)	(1.1009)
*ind_mw*boy_boy*	0.7520	– 0.3494	0.5206	– 0.6960	– 0.4030
**old_young*	(0.9637)	(0.7236)	(0.4203)	(0.8117)	(1.2331)
h†	– 0.4453*	– 0.2051	0.1549	0.1034	1.0079***
	(0.2300)	(0.2609)	(0.1697)	(0.2972)	(0.3304)
R^2	0.1408	0.1844	0.0945	0.2645	0.2385
Number of obs.	770	770	770	770	770

Note: Values in parentheses are robust standard errors.

† *h* is an augmenting term suggested by Maddala (1993, p. 121). It takes the form: $\phi(X_M\beta)/\Phi(X_M\beta)$ if *ind_mw* = 1; $-\phi(X_M\beta)/\lfloor 1-\Phi(X_M\beta)\rfloor$ if *ind_mw* = 0.

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

TABLE 6-1

Determinants of Credit Constraint and Maternal Employment: Bivariate Probit Results Treating Credit Constraint (Broadly Defined) as Endogenous

	(1)		(2)		(3)		(4)	
	Coef.	Robust Std. Error	Coef.	Robust Std. Error	Coef.	Robust Std. Error	Coef.	Robust Std. Error
A. Maternal Labor Participation Equation (Dependent Variable: *ind_mw*)								
b_cc	0.3440	1.3882	0.2671	2.5558	0.2290	1.3324	0.0366	2.2529
f_age	0.0496**	0.0222	0.0483**	0.0232	0.0363	0.0228	0.0321	0.0236
m_age	– 0.0544**	0.0266	– 0.0540*	0.0322	– 0.0399	0.0281	– 0.0368	0.0352
amales	– 0.1074	0.1056	– 0.1533	0.1380	– 0.1049	0.1079	– 0.1472	0.1382
afemales	– 0.0058	0.1257	0.0569	0.1614	0.0204	0.1235	0.0992	0.1466
boys	0.0309	0.0842	0.0149	0.0978	0.0192	0.0839	– 0.0036	0.0928
girls	0.0707	0.0839	0.0540	0.1075	0.0767	0.0865	0.0677	0.1062
infants	– 0.1014	0.1197	– 0.0411	0.1426	– 0.0909	0.1189	– 0.0326	0.1320
acr_ir	0.0222	0.0293	0.0135	0.0299	0.0269	0.0311	0.0147	0.0314
f_edu	– 0.0474	0.0354	– 0.0448	0.0441	– 0.0530	0.0359	– 0.0489	0.0400
m_edu	– 0.0103	0.0669	– 0.0087	0.0813	0.0352	0.0660	0.0471	0.0745
bullocks	0.1230	0.0919	0.1144	0.0935	0.1350	0.0964	0.1368	0.1010
hdf_lit			0.1082	0.2538			0.2342	0.2495
hdm_lit			– 1.4304	0.6681			– 1.4249**	0.7049
spf_lit			– 0.0311	0.2627			0.0125	0.2656
spm_lit			0.5112	0.9072			1.0505	0.7410
hdp_adiff			0.0157	0.0277			0.0234	0.0275
spp_adiff			0.0068	0.0301			0.0000	0.0279
scheduled caste					0.0022	0.3336	0.0235	0.4452
upper/medium Hindu caste					0.9007	0.6841	1.0146	0.8117
scheduled tribe					– 0.8099	0.5361	– 1.6482**	0.6625
Muslim					0.4590	0.6196	0.5711	0.8283
B. Credit Constraint Equation (Dependent Variable: *b_cc*)								
hd_age	– 0.0147	0.0127	– 0.0136	0.0177	– 0.0211*	0.0128	– 0.0204	0.0169
amales	0.0680	0.1208	0.0625	0.1355	0.0644	0.1214	0.0591	0.1368
afemales	0.1925	0.1402	0.1808	0.1471	0.1780	0.1428	0.1742	0.1464
emales	– 0.1585	0.5322	– 0.1853	0.9407	– 0.0898	0.5494	– 0.0889	0.9281
efemales	0.2408	0.2757	0.2387	0.4001	0.3055	0.2552	0.3190	0.2912
hhsize	0.0028	0.0439	0.0062	0.0448	0.0105	0.0431	0.0122	0.0442

landval	– 0.0698	0.0880	– 0.0790	0.1065	– 0.0417	0.0956	– 0.0504	0.1162
land2	0.0007	0.0017	0.0008	0.0019	0.0001	0.0019	0.0003	0.0022
scheduled caste					0.3486	0.2438	0.3343	0.2968
upper/medium Hindu caste					0.6543	0.5182	0.6419	0.5236
scheduled tribe					0.3500	0.4782	0.1001	0.4997
Muslim					1.2171**	0.5314	1.1931**	0.5354
Constant	0.5177	0.4732	0.4943	0.5862	0.5706	0.4769	0.5636	0.5646
ρ	0.0365	0.9107	0.0836	1.6782	0.0969	0.8568	0.1917	1.4482
No. of observations	256		241		254		239	

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

Table 6-2

Determinants of Credit Constraint and Maternal Employment: Bivariate Probit Results Treating Credit Constraint (Narrowly Defined) as Endogenous

	(1)		(2)		(3)		(4)	
	Coef.	Robust Std. Error	Coef.	Robust Std. Error	Coef.	Robust Std. Error	Coef.	Robust Std. Error
A. Maternal Labor Participation Equation (Dependent Variable: *ind_mw*)								
b_cc2	1.3859**	0.6287	1.4096**	0.5794	1.3746	1.0802	1.2906*	0.7530
f_age	0.0329	0.0245	0.0297	0.0238	0.0230	0.0315	0.0201	0.0237
m_age	– 0.0437*	0.0246	– 0.0406	0.0248	– 0.0316	0.0307	– 0.0297	0.0252
amales	– 0.1078	0.0887	– 0.1409	0.0947	– 0.1091	0.0912	– 0.1435	0.0955
afemales	– 0.0480	0.1066	– 0.0057	0.1166	– 0.0249	0.1123	0.0303	0.1261
boys	– 0.0043	0.0734	– 0.0259	0.0743	– 0.0176	0.0891	– 0.0413	0.0795
girls	0.0304	0.0697	0.0113	0.0676	0.0300	0.0867	0.0184	0.0751
infants	– 0.1038	0.0961	– 0.0518	0.1043	– 0.0976	0.0974	– 0.0428	0.1047
acr_ir	0.0132	0.0236	0.0072	0.0215	0.0175	0.0277	0.0092	0.0238
f_edu	– 0.0322	0.0271	– 0.0287	0.0271	– 0.0393	0.0306	– 0.0373	0.0298
m_edu	– 0.0311	0.0484	– 0.0340	0.0564	0.0076	0.0572	0.0172	0.0677
bullocks	0.0945	0.0848	0.0764	0.0829	0.1036	0.1092	0.0985	0.0954
hdf_lit			0.0629	0.2056			0.1948	0.2292
hdm_lit			– 1.1718	0.7480			– 1.2681*	0.7110
spf_lit			– 0.0162	0.2098			0.0242	0.2234
spm_lit			0.2775	0.7023			0.7546	0.6746
hdp_adiff			0.0204	0.0224			0.0264	0.0228
spp_adiff			– 0.0073	0.0232			– 0.0108	0.0232
scheduled caste					– 0.1834	0.2940	– 0.1742	0.2631
upper/medium Hindu caste					0.3143	0.9301	0.4283	0.6520
scheduled tribe					– 0.8541**	0.4266	– 1.4290*	0.7335
Muslim					0.1791	0.6481	0.2386	0.5597
B. Credit Constraint Equation (Dependent Variable: *b_cc2*)								
*hd_ag*e	0.0018	0.0118	0.0011	0.0116	– 0.0011	0.0195	– 0.0017	0.0160
*amale*s	– 0.0141	0.1133	– 0.0267	0.1162	– 0.0331	0.1101	– 0.0467	0.1120
afemales	0.1560	0.1365	0.1605	0.1385	0.1421	0.1556	0.1601	0.1463
emales	– 0.6723***	0.2558	– 0.6789***	0.2626	– 0.7030***	0.2495	– 0.7248**	0.2873
efemales	– 0.0499	0.2343	– 0.1113	0.2465	0.0036	0.2822	– 0.0225	0.2630

hhsize	0.0337	0.0422	0.0368	0.0429	0.0427	0.0406	0.0432	0.0409
landval	– 0.0057	0.0784	– 0.0077	0.0800	0.0304	0.0803	0.0278	0.0807
land2	– 0.0001	0.0014	– 0.0000	0.0014	– 0.0008	0.0014	– 0.0007	0.0015
scheduled caste					0.4450	0.2721	0.4208	0.2443
upper/medium Hindu caste					0.8817*	0.5005	0.8801**	0.4456
scheduled tribe					0.4134	0.4594	0.1676	0.4995
Muslim					0.5111	0.4735	0.4728	0.4643
Constant	– 0.4217	0.5006	– 0.3796	0.4897	– 0.5096	0.7429	– 0.4713	0.6341
ρ	– 0.7615	0.5136	– 0.7999	0.4645	– 0.7616	0.8580	– 0.7419	0.5449
No. of observations	256		241		254		239	

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

TABLE 7-1

Determinants of Credit Constraint and Parental Employment: Trivariate Probit Results Treating Credit Constraint (Broadly Defined) as Endogenous

	(1)		(2)		(3)		(4)	
	Coef.	Robust Std. Error	Coef.	Robust Std. Error	Coef.	Robust Std. Error	Coef.	Robust Std. Error
A. Maternal Labor Participation Equation (Dependent Variable: *ind_mw*)								
b_cc	– 0.1221	0.9918	– 0.9858**	0.4146	– 0.9367*	0.5505	1.1048	0.7874
m_age	– 0.0048	0.0116	– 0.0066	0.0116	– 0.0044	0.0117	– 0.0069	0.0089
amales	– 0.0978	0.0997	– 0.0825	0.0824	– 0.0551	0.0881	– 0.1665*	0.0964
afemales	0.1119	0.1242	0.1894*	0.1116	0.1420	0.1127	0.1340	0.1301
boys	– 0.0053	0.0982	– 0.0914	0.0900	– 0.0435	0.0849	– 0.0053	0.0862
girls	0.0777	0.0737	0.0549	0.0688	0.0821	0.0686	0.0351	0.0764
infants	– 0.1154	0.1151	– 0.0399	0.0946	– 0.0720	0.1027	– 0.0454	0.1056
acr_ir	0.0164	0.0286	0.0032	0.0187	0.0123	0.0232	0.0145	0.0259
m_edu	– 0.0762	0.0544	– 0.0431	0.0483	– 0.0293	0.0510	– 0.0113	0.0545
ind_fw	0.7434	0.7274	1.4102***	0.5237	1.0620**	0.5201	– 0.1760	0.4740
hdf_lit			– 0.0042	0.1820			0.0975	0.2185
hdm_lit			– 1.2172**	0.5300			– 1.4320**	0.7074
spf_lit			– 0.0857	0.1932			– 0.0173	0.2232
spm_lit			0.5011	0.7151			0.9327	0.5939
hdp_adiff			0.0102	0.0206			0.0244	0.0241
spp_adiff			0.0039	0.0208			– 0.0093	0.0236
scheduled caste					0.1007	0.2284	– 0.1341	0.2288
upper/medium Hindu caste					1.1451**	0.4870	0.8913	0.5600
scheduled tribe					– 0.6373	0.5841	– 1.5425**	0.6074
Muslim					0.6836	0.4539	0.1537	0.4561
B. Paternal Labor Participation Equation (Dependent Variable: *ind_fw*)								
b_cc	1.2301**	0.5306	1.3429***	0.4065	1.0290**	0.4345	1.3921***	0.5022
f_age	– 0.0031	0.0077	– 0.0043	0.0057	– 0.0011	0.0063	– 0.0057	0.0066
amales	– 0.0624	0.0841	– 0.0806	0.0775	– 0.0596	0.0880	– 0.0845	0.0859
afemales	– 0.1899*	0.1056	– 0.2009**	0.0967	– 0.1738	0.1097	– 0.1413	0.1062
boys	0.2041**	0.0866	0.2267***	0.0810	0.2016**	0.0861	0.1725*	0.0962
girls	– 0.0235	0.0764	– 0.0319	0.0770	– 0.0157	0.0779	– 0.0253	0.0744
acr_ir	– 0.0079	0.0240	– 0.0031	0.0242	– 0.0044	0.0253	– 0.0000	0.0236
f_edu	0.0179	0.0328	0.0080	0.0273	0.0052	0.0330	0.0033	0.0282

bullocks	0.1553*	0.0901	0.1248	0.0942	0.1742*	0.0942	0.1441	0.0988
C. Credit Constraint Equation (Dependent Variable: *b_cc*)								
hd_age	– 0.0147	0.0117	– 0.0173*	0.0092	– 0.0248***	0.0086	– 0.0120	0.0156
amales	0.0480	0.1166	0.0605	0.1172	0.0669	0.1081	0.0282	0.1190
afemales	0.1987	0.1401	0.1589	0.1435	0.1639	0.1500	0.1206	0.1525
emales	– 0.1925	0.3725	– 0.0665	0.3854	0.0361	0.3181	– 0.4544	0.3902
efemales	0.2925	0.2677	0.3154	0.2120	0.3742*	0.1966	0.2034	0.3078
hhsize	– 0.0010	0.0436	0.0039	0.0450	0.0148	0.0449	0.0158	0.0421
landval	– 0.0481	0.0811	– 0.0584	0.0726	– 0.0479	0.0716	0.0032	0.0978
land2	0.0004	0.0016	0.0006	0.0014	0.0004	0.0015	– 0.0004	0.0018
scheduled caste					0.2556	0.2320	0.3061	0.2609
upper/medium Hindu caste					0.6995	0.5138	0.5425	0.4553
scheduled tribe					0.5368	0.4844	0.1159	0.5287
Muslim					1.2443**	0.4995	1.2887***	0.4965
Constant	0.5610	0.4430	0.6820*	0.3786	0.6849	0.3992	0.3603	0.5724
ρ12	– 0.1159	0.5184	– 0.7407***	0.2714	– 0.4114	0.3046	0.5713*	0.3072
ρ13	0.1996	0.5556	0.6414**	0.2882	0.6469*	0.3551	– 0.5334	0.5109
ρ23	– 0.4379	0.3738	– 0.5439*	0.2929	– 0.3013	0.2803	– 0.5946	0.3754
No. of observations	256		241		254		239	

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

TABLE 7-2

Determinants of Credit Constraint and Parental Employment: Trivariate Probit Results Treating Credit Constraint (Narrowly Defined) as Endogenous

	(1)		(2)		(3)		(4)	
	Coef.	Robust Std. Error	Coef.	Robust Std. Error	Coef.	Robust Std. Error	Coef.	Robust Std. Error
A. Maternal Labor Participation Equation (Dependent Variable: *ind_mw*)								
b_cc2	– 0.0959	2.6477	1.4008***	0.4621	– 0.9559**	0.4717	1.1111*	0.6637
m_age	– 0.0057	0.0104	– 0.0071	0.0079	– 0.0091	0.0109	– 0.0065	0.0079
amales	– 0.0974	0.1193	– 0.1384	0.1061	– 0.0535	0.0841	– 0.1519	0.0954
afemales	0.1114	0.2136	0.0547	0.1319	0.1477	0.1135	0.1217	0.1286
boys	– 0.0076	0.1303	– 0.0356	0.0991	– 0.0486	0.0886	– 0.0385	0.0909
girls	0.0799	0.0811	0.0128	0.0635	0.0816	0.0699	0.0291	0.0713
infants	– 0.1207	0.1176	– 0.0645	0.1031	– 0.0678	0.1036	– 0.0511	0.1031
acr_ir	0.0155	0.0312	0.0028	0.0200	0.0130	0.0234	0.0097	0.0241
m_edu	– 0.0802	0.0552	– 0.0624	0.0501	– 0.0309	0.0505	– 0.0165	0.0553
ind_fw	0.7662	1.4497	0.0995	0.7447	1.1660**	0.5571	0.0483	0.5101
hdf_lit			– 0.0185	0.1734			0.1093	0.2149
hdm_lit			– 1.1613*	0.6976			– 1.4278**	0.7022
spf_lit			– 0.0527	0.2138			– 0.0126	0.2201
spm_lit			0.4055	0.5986			0.9193	0.5669
hdp_adiff			0.0187	0.0213			0.0260	0.0239
spp_adiff			– 0.0075	0.0218			– 0.0119	0.0238
scheduled caste					0.0952	0.2233	– 0.1385	0.2152
upper/medium Hindu caste					1.1923**	0.5250	0.8183	0.5378
scheduled tribe					– 0.6037	0.5519	– 1.5589**	0.6095
Muslim					0.5215	0.3815	0.1847	0.4362
B. Paternal Labor Participation Equation (Dependent Variable: *ind_fw*)								
b_cc2	1.1490	0.8413	1.5779***	0.3682	0.9198**	0.4351	1.3478**	0.5862
f_age	0.0004	0.0088	– 0.0023	0.0048	0.0021	0.0057	– 0.0017	0.0067
amales	– 0.0543	0.0876	– 0.0585	0.0880	– 0.0524	0.0911	– 0.0691	0.0903
afemales	– 0.1948*	0.1160	– 0.1882*	0.1103	– 0.1747	0.1134	– 0.1676	0.1152
boys	0.2025**	0.0972	0.1513*	0.0884	0.1997**	0.0883	0.1712	0.1056
girls	– 0.0227	0.0839	– 0.0444	0.0737	– 0.0066	0.0770	– 0.0238	0.0776
acr_ir	– 0.0101	0.0246	– 0.0102	0.0204	– 0.0061	0.0251	– 0.0056	0.0226
f_edu	0.0208	0.0352	0.0062	0.0282	0.0068	0.0332	0.0066	0.0297

bullocks	0.1599*	0.0905	0.1361	0.0873	0.1693*	0.0965	0.1538	0.1006
C. Credit Constraint Equation (Dependent Variable: *b_cc2*)								
hd_age	– 0.0047	0.0146	0.0004	0.0094	– 0.0136	0.0102	– 0.0050	0.0119
amales	– 0.0134	0.1208	– 0.0628	0.1369	0.0028	0.1100	– 0.0424	0.1133
afemales	0.1851	0.1429	0.1193	0.1425	0.1531	0.1502	0.1255	0.1559
emales	– 0.5548	0.5759	– 0.6742***	0.2500	– 0.3050	0.3971	– 0.7273**	0.3036
efemales	0.1423	0.3601	– 0.0653	0.3031	0.2435	0.1926	0.0476	0.2320
hhsize	0.0276	0.0439	0.0434	0.0420	0.0419	0.0438	0.0442	0.0411
landval	– 0.0298	0.0898	0.0285	0.0677	– 0.0227	0.0739	0.0388	0.0926
land2	0.0001	0.0017	– 0.0007	0.0014	– 0.0001	0.0015	– 0.0010	0.0016
scheduled caste					0.2855	0.2285	0.3201	0.2402
upper/medium Hindu caste					1.0008**	0.5110	0.7761**	0.4604
scheduled tribe					0.6065	0.4738	0.1753	0.5813
Muslim					0.5310	0.4274	0.5998	0.4438
Constant	– 0.1574	0.5169	– 0.3256	0.3732	– 0.0905	0.4403	– 0.2631	0.4440
ρ12	– 0.1219	1.1809	0.5204	0.3791	– 0.4669	0.3519	0.4715	0.3310
ρ13	0.1758	1.4783	– 0.7999***	0.3042	0.6227**	0.3119	– 0.6128	0.4256
ρ23	– 0.3965	0.6027	– 0.7377**	0.2961	– 0.2433	0.2765	– 0.5711	0.4446
No. of observations	256		241		254		239	

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