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January 2009

Abstract

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Keywords: child labor, schooling, gender bias, credit constraint, household models
JEL classification: I21, I22, J22, O12, O16

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January 25, 2009

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Abstract

Using a unique dataset obtained from rural Andhra Pradesh, India that contains direct observations of household access to credit and detailed time use, results of this study indicate that credit market failures lead to a substantial reallocation of time used by children for activities such as schooling, household chores, remunerative work, and leisure. The negative effects of credit constraints on schooling amount to a 60% decrease of average schooling time. However, the magnitude of decrease due to credit constraints is about half that of the increase in both domestic and remunerative child labor, the other half appearing to come from a reduction in leisure.

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1. Introduction

Among the many market failures that stand in the way of economic development, the most pervasive may be those credit market failures which "impede the ability of the poor to make the private or collective 'investments' they need to escape poverty" (Banerjee, Benabou and Mookherjee 2006, xv). Given this, there has been a surge of interest in recent years in investigating the effects of credit market failures on education for children, the most important investment the poor can make.

Most empirical studies in developing countries conclude that household access to credit markets has a significant effect on childhood education and on child labor. However, there appear to be two common limitations shared by most existing studies: First, datasets used in these studies do not have direct observations of access to credit markets by sample households. As a result, researchers have relied on various kinds of exogenous income shocks in order to infer effects of credit access (or relaxation of credit constraints) indirectly. Second, since data on comprehensive time use patterns of children are rarely available, many studies focus on either education (e.g. Jacoby 1994, Jacoby and Skoufias 1997; Sawada and Lokshin, 2009) or child labor (e.g. Beegle *et al* 2006). However, the effects of credit market failure on the reallocation of children's time are likely to be seen in all activities including household chores and leisure as well as schooling and remunerative work. While it has often been assumed that an increase (decrease) in hours spent in child labor corresponds to a comparable decrease (increase) in schooling hours, recent studies have found that such a correspondence is far from one-to-one (Ravallion and Wodon 2000, Edmonds 2006). These studies indicate that a major source of this imperfect substitution is likely to come from a reduction in leisure. However, the amount of time spent on leisure is not directly observed in these studies. As a result, existing research on the effects of credit access on schooling and/or child labor do not shed light on how credit access affects the burden of household production (relative to market work) on children's time or leisure.

To address this void, the present study utilizes a unique household survey dataset collected in a rural part of the Indian state of Andhra Pradesh where the incidence of child labor is found to be relatively high. This dataset contains two special modules that are typically not available in large-scale multi-purpose household surveys: (1) time use and (2) credit access. The detailed time-use module records time allocation of all household members for various activities and allows critical distinctions to be made between aspects such as time spent on schooling, remunerative work, household chores, and leisure. In addition, the credit module contains detailed information on access to credit. This in turn allows distinctions to be made between credit-constrained and unconstrained households and also facilitates modeling the determination of credit market access explicitly.

Previewing findings of the present study, results suggest that credit constraints lead to substantial reallocation of time use among children. Children in credit-constrained households tend to increase time allocated for both remunerative and domestic work. This in turn comes at the expense of time spent for schooling and leisure. This study shows that analyses of children's time allocation focusing exclusively on remunerative work and schooling, ignoring domestic work or leisure, can underestimate the ill effects of credit constraints.

The remainder of this paper is organized as follows: Section 2 includes a review of the existing literature related to credit constraints and education. The major features of the dataset used in this study are described in Section 3. Section 4 includes empirical specifications, and empirical results are provided in Section 5. Conclusions are discussed in Section 6.

2. Identifying the Effects of Credit Access on Household Behavior: A Survey

In the absence of data with direct observations of credit-constrained and unconstrained households, a conventional approach to incorporating credit constraints in empirical models is to split the sample into those who are likely to be credit-constrained and those who are not (Zeldes 1989; Morduch 1990). This exogenous approach, however, has two potential problems: First, it is unlikely that a single variable such as the income-wealth ratio or land ownership is a sufficient predictor of consumer abilities to borrow (Garcia *et al* 1997, p.158; Jappelli 1990). Second, credit constraint is endogenously generated; thus estimation results will likely suffer from endogeneity bias (Scott, 2000).

Recent empirical studies have recognized these potential issues and have relied on a variety of exogenous shocks to infer effects of credit constraints on household behavior. One approach utilizes transitory productivity shocks. The identification assumption is that a measured productivity shock generates a shift in the credit entitlement of households but is uncorrelated with household unobservables. For example, Beegle *et al* (2006) use self-reported crop shocks to identify the effects of credit constraints on child labor. However, one potential issue with their approach is that it mixes wealth and substitution effects. A productivity shock changes household shadow prices which define wealth and substitution effects. A negative farm productivity shock decreases the demand for farm production inputs while the wealth effect can increase the labor supply to farming if the outside labor opportunity is limited. This seems to be the case in the study region of Beegle *et al* where "the use of wage labor is very limited" (p.81). What this approach identifies may thus not be the effect of credit constraint, which is the marginal utility value of current wealth relative to the future, but the combined effect of price changes and ensuing wealth changes.

Edmonds (2006) exploits a pension policy change in South Africa. The idea is that a previously unanticipated wealth transfer program will shift credit entitlement of households but is uncorrelated with household unobservables. Edmonds (2006) uses a regression discontinuity design to deal with the endogeneity of pension eligibility. By controlling for household characteristics, especially age of elderly members, his estimation exploits a discrete jump in pension eligibility among observationally proximate households with elderly members. The size of transfer changes the wealth position considerably and affects the household schooling choice. While attractive, one of the major limitations of the "unanticipated shock" approach is that such events (or natural experiments more generally) do not occur very frequently.[1]

[1] There are a few additional issues in interpreting Edmond's results: First, the study yields an estimate of local effects limited to the neighborhood where the discrete jump occurs. Second, the study does not distinguish between consumptive demand of schooling and "investive" demand, as it measures the effect of

Attanasio *et al* (2008) use data on car loans and note that credit-constrained individuals exhibit a larger response to longer maturity. This is because extension of maturity effectively increases the credit limit while its impact on repayment burden is of second-order. While this novel approach has merit, it has limited applicability to less developed countries where formal loans for the purchase of consumer durables are less prevalent and non-standardized.

Another distinct approach is experimental and taken by Karlan and Zinman (2006). In this approach, credit entitlement is randomly assigned to households. This is by far the cleanest way to examine the effect of credit constraint on household choices. However, despite the obvious attractions of natural and prospective experimental approaches, their validity critically depends on specific locations and the contexts that make such experiments feasible. Unfortunately, in the setting of child labor and time allocation in rural India, the availability of such opportunities appears to be relatively limited. This paper alternatively seeks to enhance the non-experimental approach by collecting richer data. As described in the next section, a household survey questionnaire was designed to allow direct identification of credit entitlement following Scott (2000). This resolves the issue of the substitution effect mixture. For addressing the potential endogeneity issues regarding household access to credit, an instrumental variables approach was used. This is similar in spirit to Beegle *et al* (2006).

3. Data

3.1. The Household Survey in Rural Andhra Pradesh, India

Approximately 400 rural households in 32 villages in the Kurnool district of the southern Indian state of Andhra Pradesh were surveyed[2]. This study region belongs to the semi-arid tropics of the Deccan Plateau and is notorious for high risk in agricultural production (Walker and Ryan

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an exogenous wealth increase.

[2] Households were randomly selected 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

1990). The survey was conducted in February-March 2005. While this period is usually characterized by an abundant demand for agricultural labor, this particular year was marked with a drought which resulted in lower demand for farm labor. Nevertheless, numerous instances of child labor were observed. Indian states are generally very large geographically and exhibit great variation in the level of social development. Thus, peripheral state border areas where the outreach of administrative power is limited are known to accommodate a higher incidence of child labor. This is true even in relatively developed states such as Andhra Pradesh.

For these reasons, the dataset contains sample households with a higher incidence of child labor than found in other data sources originating in India. For example, 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 was used (Edmonds *et al* 2005). In UP and Bihar (LSMS dataset 1997/98), where income poverty has been more severe than in other regions of India, the child labor incidence ratio was reported to be around 28.3 percent (Sakamoto 2006). The corresponding figure for the sample used in this study was 54.2 percent (Kurosaki *et al* 2006).

3.2. Time Allocation of Children

The survey contains a "one week time use module" whose reference period is the seven days immediately prior to the interview date. Respondents were asked about their activity on each "half-day" (AM or PM) during the reference period. 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, including time spent on homework, (6)Social activities, (7) Leisure, (8)Sickness, and (9) Other.

Adopting the ILO Standards classification, children in age group 5-14 are covered in this paper. Table 1 summarizes the one week time use data for 876 children aged 5-14 included in the sample households. For empirical analysis, the nine activity groups were aggregated into four

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paper, differences in sampling probability were corrected by weighting. See Fuwa *et al* (2006a) for details.

broader categories: (1) *schooling* (category 5), (2) *household chores including child care* (category 3 & 4), (3) *remunerative work* (category 1), and (4) *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. Thus, each variable takes on integer values between 0 and 14.

Table 1 summarizes the overall pattern of time used by children in the sample for various activities. Despite the relatively high incidence of child labor in the study area, children in the sample devote the largest proportion (nearly one third on average) of their time to schooling. After schooling, the bulk of their time is split equally between remunerative work and leisure. Each of these activities accounts for approximately one quarter of time allocation. The time devoted to household chores (as a main activity at least) accounts for a relatively smaller amount (one tenth) of their time. While information/data on child schooling and remunerative work is widely available, data on child domestic work and leisure are less commonly available. However, a substantial share (38%) of time used by children in the study sample is devoted to those two types of activities. Thus, ignoring time spent for those activities may potentially lead to erroneous inferences regarding the way children allocate their time (for example, between schooling and remunerative work).

3.3. Credit Constraints

As discussed in Section 2, the credit module was designed to identify credit-constrained households directly as suggested by Scott (2000). In identifying credit constraints, household heads were asked about member experience with credit suppliers during the 12 months prior to the survey. To construct liquidity constraint indicators with sufficient variation across households, concentration was placed on formal credit sources. 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, and this generally depends on ownership of land title. Conversely, informal credit comes in numerous forms, so it is difficult to classify households according to credit access, and the determinants of access are less clear cut. Further, 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.

Whether or not a household had tried to obtain a loan in a particular period was used to identify credit-constrained households. For those who tried to borrow money, it was determined whether or not a household could borrow as much as they requested under the proposed conditions. If the answer was yes, the household was identified as unconstrained. Those households who had their loan applications rejected or who could not borrow sufficiently were identified as credit-constrained.

Those who did not try to borrow were further asked the reasons for not seeking a bank loan. The answer choices were: (1) *No need for credit*, (2) *Not want to be in debt*, (3) *Terms are not attractive (too short duration, too high interest rate, 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*, and (10) *Other*.

Respondents who chose one of (3) through (9) were identified as households likely to be credit-constrained with regard to formal sources. The remaining respondents who did not try to borrow were considered to be unconstrained. This is a "broad definition of credit constraint." However, respondents who chose one of (3) through (5) might not in fact be credit-constrained. Thus, an indicator variable was defined under the "narrow definition of credit constraint." This identified those households choosing one of (6) through (9) as constrained[3]. This narrow definition of credit constraint is the focus in subsequent empirical analysis[4]. On the basis of these responses, credit-constrained households who were *not able to* access credit can be identified[5]. Since almost

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[3] This "narrow definition" is broadly compatible with the "weaker definition" of credit constraint in Attanasio *et al* (2008). Their "weaker definition" refers to the gap in lending and borrowing rates, and options (3) through (5) in this study are transaction costs that increase it.

[4] Results of empirical analysis based on the wider definition of credit constraints are broadly similar to what is reported here.

[5] This direct inference approach cannot identify constrained households who are not in need of credit through, for example, experiencing a positive income shock. However, this limitation would also be found in

none of the existing multi-purpose household surveys include direct questions that identify credit constraints (Scott 2000), the data set provides valuable direct information for separating constrained and unconstrained households.

Table 2 shows descriptive statistics for all 331 households used in this study. Among these, 164 (49.5 percent) are identified as credit-constrained (under the narrower definition), and this indicates that a significant proportion of households are indeed credit-constrained[6]. While age and education profiles of the constrained and unconstrained 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 unconstrained households. The difference, however, is statistically significant only in the case of average household size.

Table 2 also summarizes time use patterns of children by contrasting credit-constrained and unconstrained households. Children's time allocation patterns are quite similar between credit-constrained and unconstrained households. Children in credit-constrained households, however, tend to allocate more time to household chores, and the difference is marginally significant with a p-value of 10%. This observation is consistent with the findings of Sawada *et al* (2006) and the possibility that mothers tend to work longer in credit-constrained households, and the burden of domestic work is shouldered in turn (at least in part) by their children. While the estimated mean amount of time spent on schooling, household chores, and leisure are all slightly less among children within credit-constrained households, the differences are not statistically significant. The next section includes investigation of whether or not these observations based on bivariate comparison hold when other factors are controlled.

4. The Econometric Specification

How does credit access affect time allocation among children? In order to implement an

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an experimental study in which the experimenter offers credit at random.

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

empirical assessment of this question, the conditional demand function approach of Pollak (1969) and Pitt (1997) is applied as follows:

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

where L_{hij} is the amount of time spent on activity j by child i in household h, 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). $\boldsymbol{X}_{hi}$ and $\boldsymbol{X}_h$ are vectors of child and household characteristics respectively and represent the shifters of market returns to child labor and schooling, the interest rate, and preferences. u_{hi} is a mean-zero error term. To control for differences in local market conditions and preferences, village fixed effects and community fixed effects are also included. Assuming that the effects of all covariates $\boldsymbol{X}_{hi}$ and $\boldsymbol{X}_h$ are the same between credit-constrained and unconstrained households, the coefficient α_{ccj} measures how the lack of access to credit affects time spent on various activities (j) by children. Household access to credit is determined by:

$$cc_h = 1[\boldsymbol{X}_h'\boldsymbol{\beta}_1 + \beta_2 K_h + e_h > 0] \qquad (2)$$

where 1[•] is an indicator function associated with credit constraint. K_h is the exogenous shifter of the amount of credit to which that household h has access, and e_h is a mean-zero error term which may be correlated with u_{hij}. The observed measure of K_h used in empirical implementation is the value of land held by household h. This identifying assumption or exclusion restriction follows Sawada *et al* (2006). They argue that the value of land owned by each household affects credit access, for example, through collateral value. However, it does not directly affect time allocation patterns of household members once the labor demand factor is controlled for using the physical size of irrigated land operated by the household as a determinant of time allocation. Following Angrist (2001), equations (1) and (2) were estimated by two-stage least squares with the value of owned land as the identifying instrument.

In estimating equation (1), the following types of control variables were employed: (1) individual characteristics of a child, (2) conventional household characteristics, (3) potential shifters of household preferences, and (4) village fixed effects. Their constituents are described below.

First, individual characteristics of a child include the child's age, a quadratic term to capture non-linearity of the age effect, defined as $(age - 5)^2$, and a dummy variable taking a value of one for girls.

Second, conventional household characteristics include the age of the household head (to control for the lifecycle effect), the years of schooling for the child's father, the years of schooling for the child's mother, their cross terms with the girl dummy variable to investigate the gender disparity among children, the number of household members, household composition variables (shares of various age-gender groups within the household membership: working-age males, working-age females, male children of age 5-14, female children of age 5-14, and children of age 0-4), a dummy variable for holders of ration cards given to below-poverty line households under the Public Distribution System of the Government of India, the acreage of irrigated land operated by the household, the number of bullocks owned by the household to represent livestock assets, and dummy variables for mutually exclusive community groupings based on religion and wider caste definitions (Scheduled Castes, Scheduled Tribes, upper and medium Hindu castes, and Muslim, with the reference category defined as those households belonging to the so-called "Other Backward Classes")

Third, potential shifters of household preferences are defined as variables that may influence household preferences via the process of bargaining over intra-household resource allocation. These include a dummy variable for literacy of the father of the household head, a dummy variable for literacy of the mother of the household head, a dummy variable for literacy of the father of the spouse of the household head, a dummy variable for literacy of the mother of the spouse of the household head, the difference in age between the father and the mother of the household head, and the difference in age between the father and the mother of the spouse of the household head. As McElroy (1990) argued, such extra-household environmental parameters

(EEP) are likely to enter into reduced-form demand functions if preferences of men and women differ and if their "bargaining power" is likely to be affected by such factors[7].

Finally, village fixed effects are included in the estimation to collectively control for differences in market conditions, environments, and school quality. In India, it is often claimed that Scheduled Castes and Scheduled Tribes are backward strata with less interest in education. If this is correct, the coefficients on their respective dummy variables would be expected to be positive in the equation for child labor and negative in that for schooling. Whether or not this holds even when other individual and household characteristics are controlled can be examined. The inclusion of community dummies (or more detailed caste fixed effects) may be expected to reduce possible bias due to omitted variables at the household level.

5. Empirical Results

Table 3 provides summary statistics of empirical variables, and Table 4 includes estimation results. Each column of Table 4 corresponds to a separate regression with each dependent "time spent on" variable: schooling, household chores and child care, remunerative work, and leisure. Regressions are based on a two stage least squares estimation and are accompanied by Huber-White robust standard errors[8]. Village and community dummies are also included, but for brevity, the coefficients on village fixed effects are not reported.

First stage regression results for the determinants of credit constraint, based on a linear probability model of Angrist (2001), are shown in Appendix Table 1.[9] Among the explanatory

[7] Alternative models of household decision making have been explicitly tested (for example, "unitary" versus "collective" models) with the same dataset in Fuwa *et al* (2006b).

[8] Since the dependent variables are restricted to values between 0 and 14, an obvious alternative estimation method would be tobit estimation in order to handle censoring. As Deaton (1997, 85-89) has shown, however, when heteroskedasticity and censoring are present, tobit estimation does not necessarily perform better than OLS. Given this, 2SLS was used in this study.

[9] One potential drawback of linear probability models is the possibility of predicted probabilities that are out of the 0-1 range. In this model, the maximum and minimum predicted values are 1.12 and -0.20, respectively. The total number of observations with out-of-range predicted values was not large (only 19 out of a total of 660 or about 3%).

variables, the market value of land owned by the household has a significantly negative coefficient, and the number of household members has a significantly positive coefficient. Households with fewer land assets and more household members are more likely to be under a binding credit constraint. Household demographic compositions also have significant coefficients.

Table 4 includes summaries of the estimation results of equation (1). These regressions explain child time allocation with endogenous credit constraint as well as other individual and household-level characteristics, community dummies, and village dummies as explanatory variables. Of particular interest are the effects of household access to credit on the amount of time children allocate to various activities (α_{ccj} in equation (1)). Credit constraints tend to reduce the time children spend on schooling and leisure and to increase time spent on domestic and remunerative work. In line with the conventional wisdom of the literature, credit constraints significantly reduce schooling time for children (p-value = 5.6%). With all else equal, the time spent on schooling by a child in a credit-constrained household is shorter by 1.4 days (2.9 half day units) over the one-week reference period compared to that of a child in an unconstrained household. The quantitative magnitude appears to be quite substantial, approximately 60% of average schooling time. Credit constraints also reduce leisure time for children by about 2.1 days (4.3 half day units), and such effects are statistically significant (at 4%). At the same time, children in credit-constrained households tend to spend significantly longer (p-value = 3%) time on domestic work (household chores including childcare) by roughly 1.6 days (3.3 half day units). Children in credit-constrained households tend to spend longer hours in remunerative work, also by 1.6 days (3.2 half day units). However, since the estimated standard error for the latter coefficient is somewhat larger, it is only marginally (19%) significant.

Although the coefficient of the credit constraint variable in the equation for remunerative work is not statistically significant at a conventional level of significance, the magnitude of the estimated coefficients suggests that the increase in total time spent for work, both domestic and remunerative (6.5 half day units), appears to match the amount of decrease in time spent for schooling and leisure (7.2 half day units). Thus, credit constraints appear to have significant effects on all aspects of the time allocation of children. These results are broadly consistent with recent empirical literature concerned with the relation between credit constraints and education (see for example Edmonds 2006, Jacoby 1994, Jacoby and Skoufias 1997, Sawada and Lokshin 2009). Findings in this study thus suggest that children in credit-constrained households increase their labor supply both for domestic work and for remunerative work (although the evidence for the latter is weaker).

Further, compatible with findings of Ravallion and Wodon (2000), the amount of decrease in schooling and increase in labor appear not to be symmetric. Ravallion and Wodon (2000) found that the increase in incidence of schooling due to the school stipend program was larger than the decrease in incidence of child labor (including both market and domestic work) by a factor of four (for boys) to eight (for girls). Point estimates in the present study indicate a somewhat smaller magnitude of asymmetry. The amount of increase in child labor (household chores and remunerative work) due to credit constraint (6.5 half-day units) is twice as large as the decrease in schooling (2.9 half-day units). In addition, data indicate that such a gap between the increase in child labor and the decrease in schooling is filled at the expense of leisure.

Results of this study demonstrate that bivariate comparisons such as those in Table 2 may fail to reveal some significant differences with far-reaching implications. While time allocation patterns of children are not significantly different between credit constrained and unconstrained households (with the exception of the difference in time allocated for domestic work), regression results reveal that the impact of credit entitlement is in fact quite significant when the effects of other variables (and the endogeneity of credit constraints) are controlled. Finally, first-stage results indicate that the size and structure of the household combined with the value of owned land and village fixed effects determine household credit entitlement.

Evidence indicates that there are significant gender gaps in child time allocation, even after controlling for (observable) household-level and individual-level characteristics. Compared with boys, time spent by girls on schooling and leisure is significantly shorter, while their time spent on household chores is significantly longer. The gender difference in time allocated for remunerative work, however, is not significantly different from zero (p-value = 0.29). The age effect on remunerative work is linearly positive while it is concave on schooling and convex on leisure. Despite conventional findings in empirical studies on India (Aggarwal 2004, Basu et al. 2003, Deb and Rosati 2002, Drèze and Kingdon 2001, Sakamoto 2006), the effects of parental education on child time allocation (including that on schooling) are surprisingly found to be generally insignificant. The only exception is the effect of maternal education on household chores. Better educated mothers tend to narrow the gender gap among children in time allocation to this activity. The general insignificance of the coefficient estimates for parental education may be due in part to the presence of variables capturing the education of grandparents. This is often found to be inter-generationally correlated. The literacy of the father of the household head, for example, is found to have significantly positive effects on schooling time for his grandchildren and negative effects on time allocated by his grandchildren for remunerative work. Among other household characteristics, the number of household members has a negative effect on remunerative work and a positive effect on leisure.

Effects of community dummies remain even after controlling for individual and household characteristics and village fixed effects. In the remunerative work regression, the coefficients for Scheduled Tribes, upper and medium Hindu castes, and Muslim are negative and statistically significant. This implies 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 coefficients for Scheduled Castes, upper and medium Hindu castes, and Muslim are positive and statistically significant. While the positive coefficient found for the upper and medium Hindu castes coincides with expectations, the finding that Muslim households are also more likely to send children to school (than households belonging to "Other Backward Classes") is again in contrast with the findings of Deb and Rosati (2002), Drèze and Kingdon (2001), Aggarwal (2004), and Sakamoto (2006). This may reflect the impact of civil movements in rural Andhra Pradesh to improve the social conditions of households belonging to the Scheduled Caste, Scheduled Tribe, and Muslim communities.

6. Conclusion

Using a unique data set exclusively collected in rural India, this paper presents results compatible with existing theoretical literature such as Galor and Zeira (1993) showing that credit market failure can be a significant factor preventing the poor from investing in childhood education. While such an inference is not necessarily new in the empirical literature, findings in this study are based on direct observations of household credit market access rather than indirect inference based on particular theoretical propositions. The quantitative magnitude of the negative effects of credit market failures is substantial (60% of the average schooling time) in the part of India where the survey was conducted.

Credit market failures appear to result in substantial reallocation of the use of time by children in all activities (including schooling). The magnitude of the decrease in schooling due to credit constraints is about half the amount of increase in child labor (including both remunerative and domestic work, which increase in similar magnitudes). The other half comes from the reduction in leisure. Results suggest that the direct cost of increased child labor due to credit market failures is thus not only lost time in schooling but also leisure time. While there is little in the data that shows the ultimate consequences of reduction in leisure, it may include lost time in homework or afterschool activities which may lead to the widely-discussed underachievement of primary school graduates in India. As Ravallion and Wodon (2000) note, the impact of credit constraint may be underestimated if reduction in leisure time is not considered.

References

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

Angrist, Joshua D. (2001), "Estimation of Limited Dependent Variable Models with Dummy Endogenous Regressors: Simple Strategies for Empirical Practice," *Journal of Business,* *Economics, and Statistics*, 19(1), 2-27.

Attanasio, Orazio P., Pinelopi Koujianou Goldberg, and Ekaterini Kyriazidou (2008), ``Credit Constraints in the Market for Consumer Durables: Evidence from Micro Data on Car Loans,'' *International Economic Review*, Vol. 49, No. 2 (May): 401-436.

Banerjee, A., R. Benabou and D. Mookherjee, eds. (2006). *Understanding Poverty*. Oxford University Press.

Beegle, K. R. Dehajia, and R. Gatti (2006), "Child Labor and Agricultural Shocks," *Journal of Development Economics*, 81: 80-96.

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.

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

Edmonds, E. (2006). "Child Labor and Schooling Responses to Anticipated Income in South Africa." *Journal of Development Economics*, 81: 386-414.

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): 375-397.

----- (2006b), "Gender Discrimination, Intrahousehold Resource Allocation, and Importance of

Spouse's Fathers: Evidence on Household Expenditure from Rural India," *Developing Economies* 44(4) : 398-439.

Galor, O., and J. Zeira (1993). "Income Distribution and Macroeconomics." *Review of Economic Studies*, 60: 35-52.

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.

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.

Karlan, D. and J. Zinman (2006), "Observing Unobservables: Identifying Information Asymmetries with a Consumer Credit Field Experiment," mimeo, Yale University.

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) : 440-464.

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.

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.

Pollak, Robert (1969). "Conditional Demand Functions and Consumption Theory." *Quarterly Journal of Economics*, 83: 1. 60-78.

Ravallion, M., and Quentin Wodon (2000), "Does Child Labour Displace Schooling? Evidence on Behavioural Responses to an Enrollment Subsidy." *Economic Journal*, 110. C158-C175.

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): 465-499.

Sawada, Yasuyuki and Michael Lokshin (2009), "Obstacles to school progression in rural Pakistan: An analysis of gender and sibling rivalry using field survey data," *Journal of Development Economics* 88, 335-347.

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.

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 Sample Households, Andhra Pradesh, India, 2005

Activity	Obs	Mean	Std. Dev.	Min	Max
Schooling	876	4.469	5.004	0	14
Household chores and child care	876	1.409	3.642	0	14
Remunerative work	876	3.594	5.602	0	14
Leisure	876	3.868	4.498	0	14

Notes: The sum of means across the four activity categories is not 14 due to a residual category which includes social activities, being sick, and "other activities."

Table 2: Characteristics of the Sample Households by Credit Constraint Status

	Credit Constraint Not Binding	Under Binding Credit Constraint	*t*-statistic (for the same mean)
Household-Level Characteristics			
No. of observations	167	164	
Age of the household head	44.263	44.610	-0.290
	(0.834)	(0.854)	[0.772]
Schooling years of the household head	1.832	1.628	0.584
	(0.253)	(0.241)	[0.560]
Schooling years of the household head's spouse	0.623	0.579	0.210
	(0.143)	(0.150)	[0.834]
Number of household members	7.162	8.012	-2.052
	(0.213)	(0.358)	[0.041]
Value of land owned by the household in 100,000 Rupees	1.240	0.829	1.223
	(0.314)	(0.113)	[0.222]
Per capita consumption per week in Rupees	145.693	136.167	0.578
	(9.988)	(13.167)	[0.564]
Children's Use of Time			
No. of observations	413	389	
Schooling	4.569	4.486	0.234
	(4.905)	(5.149)	[0.815]
Household chores and child care	1.228	1.650	1.634
	(3.470)	(3.857)	[0.103]
Remunerative work	3.663	3.401	0.664
	(5.728)	(5.450)	[0.507]
Leisure	3.903	3.776	0.465
	(4.328)	(4.645)	[0.642]

Notes: Numbers above show averages or t-statistics. Numbers in parentheses and brackets below show respectively standard deviations and p-values. Credit constraint status is based on the "narrow definition" described in section 3.3.

Table 3: Definition and Summary Statistics of Variables

Variable Definition (Unit)	No. of Obs.	Mean	Std. Dev.	Min.	Max.
Endogenous Variables, Child-Level					
Time spent on schooling (half-days)	876	4.469	5.004	0	14
Time spent on household chores and child care (half-days)	876	1.409	3.642	0	14
Time spent on remunerative work (half-days)	876	3.594	5.602	0	14
Leisure time (half-days)	876	3.868	4.498	0	14
Exogenous Variables, Child-Level					
Age (years)	887	10.108	2.704	5	14
Age squared ($(Age\text{-}5)^2$)	887	33.397	26.956	0	81
Girl	887	0.499	dummy	0	1
Endogenous Variables, Household-Level					
Credit constraint (broad definition)	810	0.600	dummy	0	1
Credit constraint (narrow definition)	810	0.488	dummy	0	1
Exogenous Variables, Household-Level					
Age of household head (years)	887	44.599	11.145	20	82
Schooling of child's father (years)	750	1.756	3.256	0	16
Schooling of child's mother (years)	839	0.547	1.669	0	14
Number of household members	887	7.773	3.772	3	29
Share of adult males (15-60) (%)	887	23.626	10.756	0	66.7
Share of adult females (15-60) (%)	887	21.890	9.183	0	66.7
Share of boys (5-14) (%)	887	21.572	13.526	0	66.7
Share of girls (5-14) (%)	887	22.011	14.851	0	75
Share of infants (0-4) (%)	887	5.516	8.648	0	37.5
Value of land owned by the household (100,000 Rupees)	887	0.981	3.176	0	48
Acreage of irrigated land operated by the household (acres)	887	3.256	22.342	0	500
Number of bullocks owned by the household	887	0.838	1.009	0	4
Holder of ration card for Below- Poverty-Line (BPL) households	901	0.754	dummy	0	1
Literacy of father of household head	816	0.256	dummy	0	1
Literacy of mother of household head	817	0.021	dummy	0	1
Literacy of father of household head's spouse	841	0.227	dummy	0	1
Literacy of mother of household head's spouse	840	0.010	dummy	0	1
Age difference among parents of household head (years)	817	5.168	4.979	0	30
Age difference among parents of household head's spouse (years)	828	4.670	4.555	0	25
Other Backward Classes (reference)	883	0.685	dummy	0	1
Scheduled Castes	883	0.202	dummy	0	1
Scheduled Tribes	883	0.032	dummy	0	1
Upper and medium Hindu castes	883	0.041	dummy	0	1
Muslim	883	0.029	dummy	0	1

Table 4: 2SLS Results Summary

Right-hand Side Variables	Dependent Variables: *Schooling*	*Household chores and child care*	*Remunerative work*	*Leisure*
Credit constraint (narrow definition)	-2.873*	3.298**	3.237	-4.257**
	(1.503)	(1.557)	(2.429)	(2.047)
	[0.056]	[0.034]	[0.183]	[0.038]
Age	0.342	0.418**	1.109***	-2.035***
	(0.264)	(0.202)	(0.273)	(0.265)
	[0.196]	[0.038]	[0.000]	[0.000]
Age squared	-0.092***	-0.012	-0.016	0.133***
	(0.026)	(0.021)	(0.030)	(0.026)
	[0.000]	[0.570]	[0.595]	[0.000]
Girl	-1.956***	2.774***	0.625	-1.593***
	(0.449)	(0.441)	(0.589)	(0.524)
	[0.000]	[0.000]	[0.289]	[0.002]
Age of household head	0.019	-0.009	0.015	0.022
	(0.021)	(0.022)	(0.026)	(0.021)
	[0.369]	[0.686]	[0.551]	[0.299]
Schooling of child's father	-0.097	0.124	0.055	0.091
	(0.104)	(0.078)	(0.136)	(0.110)
	[0.351]	[0.110]	[0.683]	[0.405]
*Schooling of child's father * Girl*	0.041	0.026	-0.210	0.096
	(0.114)	(0.136)	(0.171)	(0.137)
	[0.723]	[0.847]	[0.219]	[0.480]
Schooling of child's mother	0.166	0.214*	-0.252	-0.072
	(0.247)	(0.112)	(0.192)	(0.207)
	[0.503]	[0.057]	[0.191]	[0.727]
*Schooling of child's mother * Girl*	0.157	-0.346**	0.102	0.119
	(0.265)	(0.159)	(0.234)	(0.237)
	[0.552]	[0.029]	[0.664]	[0.617]
No. of household members	0.076	-0.047	-0.185**	0.170**
	(0.059)	(0.061)	(0.085)	(0.073)
	[0.197]	[0.444]	[0.030]	[0.020]
Share of adult males	0.004	0.004	0.011	-0.020
	(0.032)	(0.031)	(0.045)	(0.036)
	[0.898]	[0.903]	[0.799]	[0.570]
Share of adult females	-0.025	-0.004	-0.038	0.056
	(0.032)	(0.030)	(0.044)	(0.038)
	[0.426]	[0.903]	[0.379]	[0.133]
Share of boys	0.021	0.017	-0.025	-0.017
	(0.034)	(0.031)	(0.045)	(0.040)
	[0.533]	[0.596]	[0.589]	[0.670]
Share of girls	0.002	0.004	-0.012	-0.002
	(0.031)	(0.028)	(0.041)	(0.035)
	[0.955]	[0.888]	[0.764]	[0.962]
Share of infants	0.021	0.056	-0.026	-0.056
	(0.037)	(0.049)	(0.054)	(0.044)
	[0.559]	[0.249]	[0.634]	[0.203]
Acreage of irrigated land	0.050	0.000	-0.064	0.041
	(0.037)	(0.042)	(0.053)	(0.045)
	[0.176]	[0.999]	[0.233]	[0.360]
Number of bullocks owned	0.216	-0.011	0.281	-0.554**
	(0.233)	(0.245)	(0.275)	(0.235)
	[0.354]	[0.964]	[0.308]	[0.018]

Table 4 (continued): 2SLS Results Summary

Right-hand Side Variables	Dependent Variables *Schooling*	*Household chores and child care*	*Remunerative work*	*Leisure*
Holder of ration card	0.725	0.627	-1.344**	0.028
	(0.524)	(0.514)	(0.613)	(0.541)
	[0.166]	[0.223]	[0.029]	[0.959]
Literacy of father of household head	2.294***	0.435	-2.151***	-0.353
	(0.496)	(0.510)	(0.622)	(0.478)
	[0.000]	[0.393]	[0.001]	[0.460]
Literacy of mother of household head	-3.400*	1.036	-0.294	0.542
	(1.857)	(1.520)	(1.209)	(1.133)
	[0.067]	[0.496]	[0.808]	[0.632]
Literacy of father of household head's spouse	0.943*	-1.356***	-0.569	0.781
	(0.502)	(0.431)	(0.612)	(0.510)
	[0.061]	[0.002]	[0.353]	[0.125]
Literacy of mother of household head's spouse	-1.684	1.818	3.571***	-3.281***
	(1.607)	(1.509)	(1.227)	(1.129)
	[0.295]	[0.228]	[0.004]	[0.004]
Age difference among parents of household head	-0.113*	0.010	0.117*	-0.009
	(0.055)	(0.052)	(0.066)	(0.056)
	[0.038]	[0.848]	[0.076]	[0.875]
Age difference among parents of household head's spouse	0.125**	-0.012	-0.021	-0.100*
	(0.054)	(0.054)	(0.062)	(0.056)
	[0.022]	[0.825]	[0.736]	[0.075]
Scheduled Castes	1.170*	-0.959	-1.109	1.250*
	(0.630)	(0.596)	(0.818)	(0.729)
	[0.063]	[0.108]	[0.175]	[0.087]
Scheduled Tribes	0.034	1.729*	-4.418**	3.154*
	(1.472)	(1.047)	(2.065)	(1.755)
	[0.982]	[0.099]	[0.032]	[0.072]
Upper and medium Hindu castes	2.163**	-1.169	-3.961***	2.694*
	(1.024)	(1.087)	(1.237)	(1.610)
	[0.035]	[0.283]	[0.001]	[0.094]
Muslim	3.413***	0.065	-3.113**	-0.269
	(1.187)	(1.240)	(1.328)	(1.186)
	[0.004]	[0.958]	[0.019]	[0.821]
No. of observations	660	660	660	660
R^2	0.316	0.162	0.268	0.248
F	9.616	2.097	6.111	6.528

Notes (1) The symbols ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.
(2) Standard errors and p-values are respectively in parentheses and square brackets.
(3) "Credit constraint" is an endogenous variable. Models include all explanatory variables defined in Table 3 except for "Value of owned land" which is excluded for identification purposes.
(4) Village fixed effects are also included, but coefficients are not reported.
(5) Weighted linear models are estimated to correct for the difference in sampling probability.

Appendix Table 1. First-Stage Regression Results of the Linear Probability Model: Determinants of Binding Credit Constraints

Dependent Variable = *Credit constraint (narrow definition)*

	Coefficient	Standard Error
Age	-0.027	0.026
Age squared	0.003	0.003
Girl	-0.045	0.049
Age of household head	-0.002	0.002
Schooling of child's father	-0.020*	0.011
*Schooling of child's father * Girl*	0.027*	0.014
Schooling of child's mother	-0.006	0.027
*Schooling of child's mother * Girl*	0.009	0.030
No. of household members	0.019***	0.006
Share of adult males	0.007*	0.004
Share of adult females	0.008**	0.003
Share of boys	0.011***	0.003
Share of girls	0.010***	0.003
Share of infants	0.012***	0.004
Acreage of irrigated land	0.003	0.005
Value of land owned	-0.022***	0.004
No. of bullocks owned	0.032	0.028
Holder of ration card	0.083	0.058
Literacy of father of household head	0.022	0.053
Literacy of mother of household head	-0.120	0.232
Literacy of father of household head's spouse	0.023	0.051
Literacy of mother of household head's spouse	-0.168	0.178
Age difference among parents of household head	-0.008	0.006
Age difference among parents of household head's spouse	-0.001	0.006
Scheduled Castes	0.152**	0.062
Scheduled Tribes	0.282*	0.163
Upper and medium Hindu castes	0.192	0.156
Muslim	0.372***	0.103
No. of observations	660	
R^2	0.2795	
F	9.56	

Notes: (1) Village dummies are also included but suppressed in the table.
(2) The symbols ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.