# The Effect of Early Childhood Malnutrition on Child Labor and Schooling: Theory and Evidence*

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*Abstract*

This paper examines how physical stature of a child measured in terms of age standardized height influences his/her selection for family labor activities vs. schooling in rural Ethiopia using malnutrition caused by exposure to significant weather shocks in early childhood as sources of identification for the child's physical stature. I estimate parametric and semi-nonparametric bivariate models for child labor and schooling. I find no evidence that better physical stature of the child leads to his/her positive selection for fulltime child labor activities. On the other hand I found reasonably strong and consistent evidence that physically more robust children are more likely to combine child labor and schooling than physically weaker children. The results are consistent across two different cohorts of children and two different identification strategies. The findings indicate that, although better early childhood nutrition leads to higher chances of attending school, it may also put the child at additional pressure to participate in family labor activities which may be reflected in poor performance in schooling. Therefore, policies that try to promote schooling through nutrition support programs could be more successful if they are accompanied by programs that could mitigate the family's needs for child labor like income support schemes.

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## 1. Introduction

Unlike the developed economies where short-term fluctuations in household income and living standards are largely associated with the conditions in the labor market and business

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cycles, temporary changes in livelihoods of rural communities in the least developed economies are often caused by changes in weather conditions. In such communities, large and unexpected changes in weather conditions can sometimes have a devastating impact on income, consumption, assets, health and survival of households and their members. Drought, flooding, hailstorms, cyclonic storms, and frost are some of the weather related shocks that frequently affect the livelihoods of rural communities in developing countries. A large number of studies have investigated the impacts of such shocks and how households try to cope with their effects. The overall picture that emerges from the multitude of empirical studies is that the ultimate impact of a shock on the well-being of a household and its members depends on a number of household and community-specific characteristics such as liquidity constraints, wealth status, and the nature and capabilities of social support networks to which households belong (see Townsend 1995; Murdoch 1999; Carter and Maluccio 2003).

One important indicator of the capability of households to absorb the effects of a shock is whether the nutritional status of its members, as reflected in anthropometric health measures, substantially deteriorates as a result of the shock. While some evidence shows that adults may lose some body mass (Dercon and Krishnan 2000) as a consequence of shocks, the majority of empirical studies show that it is children in their first 3 years of life at the time of the shock who are particularly vulnerable. This is not surprising given that this is a period when children are growing fast and have high nutritional requirements per unit of body mass (Martorell et al. 1995; Martorell 1999; Hoddinott and Kinsey 2001). Another reason for the high nutrition requirements for young children is their vulnerability to diseases because of immature immune systems and the inability to make their needs known.

Some studies have examined the extent to which exposure to a shock at this early age affects the physical stature of the person later in life. While some evidence from the United States shows that reversal of the effects of early malnutrition is possible if there are dramatic favorable changes in the environment for the child at the appropriate time (Golden 1994), studies from developing countries (e.g., Alderman, Hoddinott and Kinsey 2006) show that victims of severe shocks in early childhood often sustain long-lasting deficiencies in their physical stature and possibly cognitive ability (Dasgupta 1997). Other studies have looked at how the effects of malnutrition on the child's health stature may be related to the child's schooling outcomes (e.g., Behrman and Lavy 1994; Glewwe and Jacoby 1995; Glewwe and King 2001; Glewwe, Jacoby and King 2001; Alderman et al. 2001) and largely find that preschool malnutrition has negative effect on a child's school enrollment and academic performance. One of the often stated reasons for this relationship between schooling and early childhood malnutrition (stunting) is that families are unwilling or hesitant to send a physically unfit child to school, in addition to the effect of childhood malnutrition on cognitive development that may be reflected in his/her poor performance or progress at school.

The largely uneducated parents in developing countries, however, may be less likely to recognize the potential correlation between physical fitness and cognitive abilities than they are to recognize the importance of a child's physical strength for family labor. Consequently, parents may end up sending the physically weaker children to school and keep the robust ones for family labor or demand more of their after school time for family labor activities. As a result, studies that ignore the importance of physical stature for child labor (where child labor also matters) may end up with results that understate the effect of malnutrition on enrollment but overstate malnutrition's effect on school performance. This is so because it is largely the weaker children with potentially lower cognitive abilities (since malnutrition also hampers child's cognitive development, Dasgupta 1997) who would be sent to school. Equity considerations may reinforce the possibility of sending a physically weaker child to school over a stronger sibling if parents feel that the weaker child will have a hard time succeeding in the labor market if he/she doesn't acquire additional skills. Therefore, understanding the role of physical stature of a child in the family's choices between schooling and child labor is not only an important research question in itself but also may help to refine and better understand the observed relationships between childhood malnutrition shocks and academic performance. One issue in using child's physical stature as a covariate in the schooling and child labor equations, however, is that it could be endogenous in both equations because parents might have been making child nutrition decisions in anticipation of specific role for the child. Therefore, an exogenous source of variation in nutritional status that is beyond the control of the parents is needed to identify its effect on schooling and child labor.

In this paper I use two sources of exogenous variation in availability of food (and possibly other amenities) during the critical ages of the child to jointly analyze the effect of early childhood malnutrition on schooling and child labor.[1] First I exploit the natural experiment generated by a massive drought in Ethiopia in 1984 that resulted in a devastating famine that killed about a million people in the country (Jansen, Harris and Penrose 1987). Second, I use the considerable annual fluctuations in rainfall in some localities in the country to identify local weather shocks and the subsequent food deficits in the areas and use these as exogenous sources of malnutrition. In Ethiopia about 85% of the people live on a subsistence agriculture that is almost fully dependent on rainfall conditions. As a result rainfall failures often have big effects on the welfare of households and their members. While grown-ups and older children might also suffer under famines and may sustain some long-term deficiencies in their health and fitness, there is a general consensus in the literature that it is the children at the early years of their life that sustain the biggest long-term damage in their stature and possibly cognitive abilities (Dasgupta 1997). The key purpose of this paper is, therefore, to examine how potential deficiencies in physical stature sustained from early childhood malnutrition are reflected in the child's participation in schooling and family labor.

The rest of the paper is organized as follows. A simple theoretical model presented in the section 2 demonstrates the effect of physical stature on child activity choice. Section 3 presents empirical models, identification strategies as well estimation methodology. The data used in empirical analysis are described and summary statistics are presented in section 4. Section 5 presents empirical results while section 6 concludes.

## 2. Theory

The basic research question in this paper can be described in a simple household utility maximization model for a family with one child and unified preferences as in Ravallion and Woodon (2000) and Bacolod and Ranjan (2008) among others. For convenience the child's life

[1] Porter (2007) analyzed the effect of the 1984 drought shock on the long-term indicators of child nutrition health using data from the first round of the Survey that I'm using. But the first stages of my empirical models in this paper expand her analysis by estimating the effects of localized rainfall shocks on the long-term nutritional status using data from a different cohort of children.

is classified into three periods: preschool age, school age and post-school age. In the preschool period, the parents invest in the health of the child in the form of nutrition, health care and other treatments. The health of the child in this period could also be influenced by factors beyond the control of the family like weather shocks and availability of health care services. In the second period parents decide whether to send the child to school or to child labor. In the third period, the child works and earns his/her own income, while parents retire and consume the return on the assets they saved during the earlier periods and possible transfers from their children. The focus here is on the decision problem that parents face in the second period given the outcome of their decisions in the first period.

Assuming that parents are altruistic towards their children and the utility parents derive from own consumption is linearly separable from that they derive from the child's utility as in Barro and Becker (1986), Cigno and Rosati (2005) and Dillon (2008), among others, the parents' utility may be stated as

$$U = \sum_t u_t(c_t^p) + \beta U^*(c_1^c, c_2^c, y_3) \qquad t=1, 2, 3 \qquad (1)$$

where, $c_t^p$ is parents' consumption in period $t$, $U^*$ is child's maximized utility, $c_1^c$ is child's consumption in period 1 including healthcare, $c_2^c$ is child's consumption in period 2 including healthcare but excluding school expenses, $y_3$ is child's income in the post-school period and $\beta$ is a measure of parental altruism towards the child where $0<\beta\leq 1$. Both $u_t(.)$ and $U^*(.)$ are assumed to be quasi-concave and strictly increasing in all of their arguments. In period 2, $c_1^p$ and $c_1^c$ are no longer part of the decision problem of the parents. However, $c_1^c$ determines the child's pre-school stock of human capital in the form of physical stature and cognitive ability, given the child's genetic and natural endowments. And according to the literature on nutrition physical stature at the preschool age (that is also correlated with cognitive ability) is a strong predictor of the later physical stature of the child as previously discussed. Let $h_1$ denote this preschool physical stature of the child measured in terms of height-for-age. Assuming that the trajectory for the physical human capital of the child is completely set in the preschool age and building on Glewwe (2002), the human capital production function of the child in period 2 may be stated as

$$h = \gamma(h_1, \mu) s(T_c^s, Q) \qquad (2)$$

where, $\gamma(.)$ is the 'learning efficiency' of the child that depends on the unobserved factors $(\mu)$ that include genetically inherited ability, child's motivation, etc. as well as the child's physical fitness accumulated during the preschool period ($h_1$). On the other hand, $s(.)$ is the schooling production function that depends on the amount of child's time spent in schooling and studying, $T_c^s$, and a vector of other educational inputs and school characteristics, Q. In period 2, $\gamma(.)$ is assumed to be predetermined while the interaction between $\gamma(.)$ and $s(.)$ produces new human capital. For simplicity accumulation of long-term human capital is assumed to be independent of fluctuations in consumption after the preschool period. That is why $c_2^c$ is not included as an argument in human capital production function for period 2.

The human capital the child accumulates through period 2 along with the net parental transfers determines his/her income in the post school period, $y_3$:

$$y_3 = \omega h - m \tag{3}$$

where $m$ is the amount of net transfers a child makes to his/her parents in the post school period and $\omega$ is the return to human capital. Family income in period 2, $y_2$, comes from three sources. For a typical agricultural household in a developing country like Ethiopia, the principal source of income is family production where both adult and child labor are used as inputs. The other potential sources of income for agricultural households include wage earnings and remittances. Letting $w_p$ and $w_c$ be the opportunity costs of the parent's time and child's time, respectively, the total family income in period 2 is given as,

$$y_2 = q(T_p^f, T_c^f \mid K) - w_p T_p^f - w_c(h_1) T_c^f + w_p T_p^w + R \tag{4}$$

where $q(.)$ is the total value of family production, $T_p^f$ is parent's time in family production, $T_p^w$ is parent's time in wage employment, $T_c^f$ is child's time in family production, $K$ is a vector of family assets like land and livestock, and $R$ stands for family income from other sources including remittances . Wage employment for the child during the school period is assumed away for the child which is generally true in the rural Ethiopian context. As such, the child's opportunity cost of time in period 2, $w_c$, is his/her marginal product in family production and it is assumed to depend on the child's physical fitness developed in period 1. In other words, $w_c$ is the return (in period 2) to the physical human capital of the child built in period 1. For simplicity, hired labor and non-family labor are also assumed away although cases of the latter may be observed even in subsistence agriculture mainly because of labor-sharing arrangements. Now, letting $p$ represent a vector of prices for the other educational inputs, the cost function for schooling can be derived following the standard procedure for deriving cost functions (for details see Cigno and Rosati 2005, 31-32). Assuming that the production function for schooling stated as equation 2 is homogenous and twice continuously differentiable, we can minimize the cost of inputs, $X$, subject to a given level of schooling $\bar{s}$ as

$$\min_{T_c^s, Q} X = w_c(h_1) T_c^s + pQ \qquad S.T. \qquad s(T_c^s, Q) = \bar{s} \tag{5}$$

This gives us the conditional cost function for schooling, $X(s, w_c(h_1), p)$ where the cost of schooling depends on the input prices and the level of schooling. $X(.)$ is assumed to exhibit the standard properties of a cost function. Then, normalizing the price of consumption goods to 1, the budget constraint for period 2 can be stated as,

$$y_2 = c_2^p + c_2^c + X(s, w_c(h_1), p) + A \tag{6}$$

where $A$ represents parental savings part of which may be transferred to the child in the post school period and $y_2$ is given by equation 4. In period 3 parents retire and live on the returns from their savings from the earlier period and transfers from the child if m is positive. Therefore, the parent's budget constraint for period 3 can be stated as:

$$c_3^p = rA + m \tag{7}$$

where *r* is return on parental assets. The net parental transfers could be positive if child-to-parent transfers exceed parent-to-child transfers. Substituting 7 and 3 for $c_3^p$ and $y_3$ in equation 1 respectively, and then substituting equation 2 for *h* the family's utility function in period 2 can be rewritten as,

$$U = u_2(c_2^p) + u_3(rA + m) + \beta U^*(c_2^c, \omega\gamma(.)s(T_c^s, Q) - m) \tag{8}$$

Note that $u_1(.)$ is no longer relevant in period 2 and hence ignored. Assuming that the non-negativity constraints for consumption and parental savings are non-binding and also assuming that the time constraint for both the parents and the child is non-binding so that the Lagrangian multipliers on all these constrains are 0, we can maximize[2] 8 subject to 6 to obtain the conditions that determine parental decisions on consumption, savings and time use for themselves and for the child. The Lagrangian function for the maximization problem is,

$$\begin{aligned}\max_{c_2^p, c_2^c, A, T_c^s, T_c^f, T_p^w, T_p^f, Q} L = {} & u_2(c_2^p) + u_3(rA + m) + \beta U^*(c_2^c, \omega\gamma(.)s(T_c^s, Q) - m) \\ & + \lambda[q(T_p^f, T_c^f \mid K) - w_p T_p^f - w_c(h_1)T_c^s + w_2^p T_p^w \\ & + R - c_2^p - c_2^c - X(s, w(h_1), p) - A]\end{aligned} \tag{9}$$

The first order conditions that are relevant for the purpose at hand are,

$$c_2^p: \qquad \frac{\partial u_2(.)}{\partial c_2^p} - \lambda = 0 \tag{10}$$

$$c_2^p: \qquad \frac{\partial u_3(.)}{\partial c_3^p}\frac{\partial c_3^p}{\partial A} - \lambda = 0 \Rightarrow r\frac{\partial u_3(.)}{\partial c_3^p} = \lambda \tag{11}$$

$$c_2^c: \qquad \beta\frac{\partial U^*(.)}{\partial c_2^c} - \lambda = 0 \tag{12}$$

$$T_c^s: \qquad \beta\gamma(.)\frac{\partial U^*(.)}{\partial y_3}\frac{\partial y_3}{\partial h}\frac{\partial h}{\partial s}\frac{\partial s}{\partial T_c^s} - \lambda\frac{\partial X}{\partial s}\frac{\partial s}{\partial T_c^s} = 0$$

$$\Rightarrow \beta\omega\gamma(.)\frac{\partial U^*(.)}{\partial y_3}\frac{\partial h}{\partial s} = \lambda\frac{\partial X}{\partial s} \tag{13}$$

$$T_c^f: \qquad \lambda[\frac{\partial q}{\partial T_c^f} - w_c(h_1)] = 0 \Rightarrow MP_{T_c}^f(T_c^f \mid K, T_p^f) = w_c(h_1) \tag{14}$$

Condition 14 states that the marginal product of the child's time in family production in period 2 equals the opportunity cost of the child's time that itself is assumed to depend on the child's physical fitness accumulated during the preschool period. In 13 $\partial X/\partial s$ is the marginal

[2] In writing the maximization problem without the expectations operator, we are assuming that parents face no uncertainty about the values of the third period variables like the return to human capital.

cost of schooling that is henceforth denoted by $MC_s$ and $\partial h / \partial s$ is the marginal productivity of schooling in the production of overall human capital henceforth denoted by $MP_s^h$. The marginal cost of schooling depends on the level of schooling, the opportunity cost of the child's time and price of other educational inputs. Dividing 10 by 11 we obtain,

$$MRS_{c_3,c_2}^{p} = \frac{\partial u_2(c_2^p) / \partial c_2^p}{\partial u_3(rA+m) / \partial c_3^p} = r \qquad (15)$$

The middle term in 16 is the marginal rate of inter-temporal substitution between current consumption and future consumption for the parents ($MRS_{c_3,c_2}^{p}$). The equation states that parents save for their future consumption until the marginal utility of the current consumption relative to their future consumption is equated to the return on savings (the interest rate). The analogous condition for the child is obtained by dividing 12 by 13,

$$MRS_{y_3,c_2}^{c} = \frac{\partial U^*(c_2^c, \omega\gamma(.)s(T_c^s, Q) - m) / \partial c_2^c}{\partial U^*(c_2^c, \omega\gamma(.)s(T_c^s, Q) - m) / \partial y_3} = \omega\left(\frac{\gamma(.)MP_s^h}{MC_s(s, w_c(h_1), p)}\right) \qquad (16)$$

The middle term in 16 is the marginal rate of inter-temporal substitution between current consumption and future income for the child ($MRS_{y_3,c_2}^{c}$). The term in the parenthesis on the right hand side of this equation may be interpreted as the marginal return to investment in schooling in terms of building the overall human capital of the child. The entire term on the right hand side then represents the marginal return to human capital built through schooling. Note that the effectiveness of investment in schooling in building the overall human capital (knowledge and capability) of the child depends on the learning efficiency of the child and marginal productivity of schooling in the production of human capital. While some of the learning efficiency could be genetic and may be acquired through inheritance, part of it is built through investment in nutrition and healthcare during the preschool period. However, it is assumed that parents treat these as sunk costs when they make decisions about consumption and time use in period 2.

Assuming that parents try to allocate the family's resources so as to maximize the life time utility for themselves and the child and given that total utility is strictly increasing in both the parents' and the child's consumption, they will allocate the child's time between $T_c^s$ and $T_c^f$ by comparing the future marginal return to investment in human capital (given by the right hand side of 16) to the return that the child's contribution to the current income could bring in if it were to be saved for future consumption (r). If $r > \omega[\gamma(.)MP_s^h / MC_s]$, then parents are likely to allocate more of the child's time to generating current income through child labor and less to schooling since marginal return to asset savings is greater than the marginal return to human capital. On the other hand, if $r < \omega[\gamma(.)MP_s^h / MC_s]$, then parents are likely to allocate more of the child's time to schooling and less to family work since marginal return to human capital in the future is greater than the marginal return to savings. Therefore, the optimal allocation of the child's time between schooling and current income generating activities is given by,

$$MRS^{c}_{y_{3},c_{2}} = \omega\left(\frac{\gamma(.)MP^{h}_{s}}{MC_{s}(s, w_{c}(h_{1}), p)}\right) = r = MRS^{p}_{c_{3},c_{2}} \tag{17}$$

A situation where a child is full-time student is a discrete case that may arise because of a very high marginal return to investment in schooling relative to the return from savings that could be made from potential contribution of the child to the current income. Similarly, a situation where a child works full time could arise because of a very high return to the child's current contribution to income compared to the anticipated marginal return to schooling. In practice, the possibility of observing these discrete cases is often high due to the fact that schooling requires some minimal level of time commitment from the child and the perfect continuity in time allocation presumed under the solutions above may not hold.

The influence of my key variable of interest, preschool physical fitness ($h_1$), on the parental decisions about the child's time allocation comes in through its effect on the marginal return to human capital. And $h_1$ affects the marginal return to human capital through its effect on the marginal cost of schooling, efficiency of learning and marginal productivity of schooling in the production of human capital. For a given $\omega$, therefore, the net effect of a higher value of $h_1$ on the return to investment in human capital depends on the relative strength of the following two effects.

$$\left(\frac{\partial MC_{s}}{\partial w_{c}}\frac{\partial w_{c}}{\partial h_{1}}\right) \quad ? \quad MP^{h}_{s}\left(\frac{\partial \gamma}{\partial h_{1}}\right) + \gamma(.)\left(\frac{\partial MP^{h}_{s}}{\partial \gamma}\frac{\partial \gamma}{\partial h_{1}}\right) \tag{18}$$

The term to the left of the question mark in 18 represents the effect of $h_1$ on the marginal cost of schooling. This comes in through the marginal productivity of the child in family production activities. The higher the value of $h_1$ the more productive the child will be in the family activities and the higher will be the value of his/her $w_c$. Therefore, a higher $h_1$ leads to higher marginal opportunity cost of schooling and the sign of the term to the left of the question mark is positive. This tends to reduce the marginal return to investment in human capital. Mathematically, this is easy to see since $MC_s$ is in the denominator of the expression for marginal return to investment in human capital in equation 17.

On the other hand, the expression to the right of the question mark in 18 represents the effect of $h_1$ on learning efficiency and marginal productivity of schooling in building human capital. The term $\partial\gamma(.)/\partial h_1$, captures the effect of physical fitness on the learning efficiency of the child that is assumed to be positive because of the empirically observed positive relationship between physical stature and cognitive ability. Note that learning efficiency is important in learning knowledge and skills not only at school but also outside the school environment and $\partial\gamma(.)/\partial h_1$ represents the effect of $h_1$ on this overall effectiveness in learning knowledge. The second term on the right captures the effect of $h_1$ on the marginal productivity of schooling in building human capital and this comes in through the effect of $h_1$ on the learning efficiency. Higher value of $h_1$ leads to more effectiveness in learning that itself is expected to improve productivity of schooling in building human capital rendering the sign of the entire expression to the right of the question mark to also be positive. Therefore, higher $h_1$ tends to boost return to investment in human capital through its effect on $\gamma(.)$ and $MP^{h}_{s}$ since both of these terms are in the numerator of the expression for the return to investment in human capital stated under equation 17.

The net effect of $h_1$ on the marginal return to investment in human capital will be negative if its effect on $MC_s$ is stronger than its combined effect on γ(.) and $MP_s^h$. For given values of $r$, $\omega$ and parental preferences, therefore, parents will have an incentive to keep a physically stronger child out of school so as to engage in the child labor activities. This means, parents believe that the marginal productivity of such a child in the current family activities is higher than whatever future gains (net of the cost of schooling) in earnings the child could achieve through schooling. On the other hand, if the combined effect of $h_1$ on the overall efficiency of learning and the marginal productivity of schooling is stronger than its effect on $MC_s$, parents will have an incentive to send the child to school. Whether parents allow the child to be a full time student by letting him/her to focus on studying even after coming back from attending school or ask him/her to work after school can be established following similar reasoning. This is so because studying after school is part of the human capital building process whose opportunity cost could be measured by the marginal productivity of the child in family activities just like attending school. Therefore, the effect of physical stature of the child on child labor and schooling is theoretically ambiguous as opposed to the prevailing wisdom that it enhances the chances of attending school.

To empirically test the implications of this theoretical model, we need to derive the parental demand functions for own and child's consumption as well as time use. When specific structural forms are assumed for the utility function, specific forms for the demand functions can be derived by simultaneously solving the relevant first order conditions stated above and the budget constraint stated under 6. For a general form of the utility function assumed here, however, the demand functions will take the following general forms.

$$T_c^{s*} = T_C^s(\omega, h_1, p, R, w_p, m, r, \mu) \tag{19}$$

$$T_c^{f*} = T_c^f(\omega, h_1, p, R, w_p, m, r, \mu) \tag{20}$$

The demand functions for other choice variables $c_2^{c*}$, $c_2^{p*}$, $T_p^{f*}$, $T_p^{w*}$, $A*$ and $Q*$ take similar general forms. It is important to note that these demand functions are interdependent because of the simultaneous nature of parental decisions. This is particularly magnified in the case of time use decisions because of the fixed time constraint. For a child constrained with only 24 hours a day, more time for family labor means less time for attending school and studying then after. Therefore, joint estimates of the demand functions will generally provide more accurate estimates of the effects of the covariates on each of the parental choices than the estimates from independent equations for each demand function. This is so because some of the factors that influence parental decisions may not be observable and hence cannot be included as regressors in each equation. As a result the errors that include these unobservables will be correlated across equations and joint estimation techniques that exploit these correlations will lead to more accurate estimates.

To specify such joint empirical models for parental demand for child labor and schooling we first define the indirect utility function for the parents, $v(\omega, h_1, p, R, w_p, m, r, \mu)$, by successively substituting the relevant demand functions into 2, 3, and 7 and the resulting functions into 8 along with $c_2^{c*}$ and $c_2^{p*}$. The indirect utility function is thus defined in terms of observables. From the researcher's perspective, however, there are unobservable elements that may influence parents' decisions and restating the utility function by adding these random components to the indirect utility provides the basis for the empirical model specified in the next section.

### 3. Econometric Models and Estimation Methodology

The main purpose of this paper is to analyze the effect of physical stature of a child in the form of height-for-age z-scores on his/her participation in child labor and schooling. The empirical model for the analysis has to allow for the potential correlation between the error terms of the schooling and child labor equations that arises because of the joint nature of the two decisions. Such a model can be specified by adding unobserved random components to the indirect utility parents derive from child schooling and work as,

$$u_{is}^{*} = v_{is}(.) + \varepsilon_{is} \tag{21}$$

$$u_{iw}^{*} = v_{iw}(.) + \varepsilon_{iw} \tag{22}$$

where $v_{is}(.)$ and $v_{iw}(.)$ denote maximized utilities from schooling and child work from the theoretical model, $\varepsilon_{is}$ and $\varepsilon_{iw}$ denote the corresponding random components, $u_{is}^{*}$ and $u_{iw}^{*}$ represent additive random utility (Cameron and Trivedi 2005) parents derive from child i's participation in schooling and family work , respectively. Assuming that $v_{is}(.)$ and $v_{iw}(.)$ are linear in their arguments, 21 and 22 can be restated as,

$$u_{is}^{*} = x_{is}^{'}\beta_s + \varepsilon_{is} \tag{23}$$

$$u_{iw}^{*} = x_{iw}^{'}\beta_w + \varepsilon_{iw} \tag{24}$$

where $x_{ij}^{'}$ represents a vector of covariates including my key variable of interest, physical stature of the child ($h_1$). The latent variables, $u_{is}^{*}$ and $u_{iw}^{*}$, are unobserved but let's assume that parents send a child to school or work only when the overall utility from doing so is positive. Then we can define the following dichotomous variables for child's participation in schooling and family work, respectively.

$$s_i = \begin{cases} 1 & if \ u_{is}^{*} > 0 \\ 0 & if \ u_{is}^{*} \leq 0 \end{cases} \tag{25}$$

$$w_i = \begin{cases} 1 & if \ u_{iw}^{*} > 0 \\ 0 & if \ u_{iw}^{*} \leq 0 \end{cases} \tag{26}$$

The four possible choices parents can make regarding child i's time use are: $s_i=0, w_i=0;$ $s_i=0, w_i=1;$ $s_i=1, w_i=0;$ and $s_i=1, w_i=1$. Assuming that $\varepsilon_{iw}$ and $\varepsilon_{is}$ are distributed jointly normal with means zero, variances one, and correlation $\rho$, the probabilities of observing each of these joint outcomes can be specified as bivariate normal. For example, the probability of observing $s_i=1$, $w_i=1$ can be stated as,

$$\begin{aligned} p_{ik} &= p[s_i = 1,\ w_i = 1] \\ &= p[u_{is}^* > 0,\ \ u_{iw}^* > 0] \\ &= p[\varepsilon_{is} < x_{is}^{'}\beta_s,\ \ \ \varepsilon_{iw} < x_{iw}^{'}\beta_w] \\ &= \int_{-\infty}^{x_{is}^{'}\beta_s} \int_{-\infty}^{x_{iw}^{''}\beta_w} \phi(z_s, z_w, \rho) dz_s dz_w \\ &= \Phi(x_{is}^{'}\beta_s, x_{iw}^{'}\beta_w, \rho) \end{aligned} \tag{27}$$

where $\phi(.)$ and $\Phi(.)$ are the standardized bivariate normal density and the cumulative density function for $(z_s, z_w)$, respectively. We can state similar bivariate cumulative density and density functions for the other three possible outcomes. Following Green (2007), these can be generalized as,

$$\begin{aligned} p_{ik} &= p[s_i = j,\ w_i = k] \\ &= \Phi(\delta_{is} x_{is}^{'}\beta_s, \delta_{iw} x_{iw}^{'}\beta_w, \delta_{is}\delta_{iw}\rho) \end{aligned} \tag{28}$$

where the indicator function $\delta_{is}=1$ if $s_i=1$ and $\delta_{is}=-1$ if $s_i=0$. Similarly, $\delta_{iw}=1$ if $w_i=1$ and $\delta_{iw}=-1$ if $w_i=0$. Then the log-likelihood function for the bivariate probit model can be stated as,

$$\ln L = \sum_i \ln \Phi(\delta_{is} x_{is}^{'}\beta_s, \delta_{iw} x_{iw}^{'}\beta_w, \delta_{is}\delta_{iw}\rho) \tag{29}$$

The model under 29 is estimated using maximum likelihood procedure. I also estimate a semi-nonparametric bivariate model for child schooling and labor using the procedure developed in Gallant and Nychka (1987). In their approach, as slightly modified by De Luca (2008), the unknown joint density of the errors is approximated by the Hermite series of the form,

$$h(\varepsilon_s, \varepsilon_w) = \frac{1}{\psi_N} \alpha_r(\varepsilon_s, \varepsilon_w)^2 \phi(\varepsilon_s)\phi(\varepsilon_w) \tag{30}$$

where, $\phi(.)$ is the standardized Gaussian density, $\alpha_r(\varepsilon_s, \varepsilon_w) = \sum_{i=0}^{r_1} \sum_{j=0}^{r_2} \alpha_{ij} \varepsilon_s^i \varepsilon_w^j$ is a polynomial in $\varepsilon_s$ and $\varepsilon_w$ of order $r=(r_1,r_2)$ and, $\psi_N = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \alpha_r(\varepsilon_s, \varepsilon_w)^2 \phi(\varepsilon_s)\phi(\varepsilon_w) d\varepsilon_s d\varepsilon_w$ is a normalization factor that ensures h(.) integrates to 1. Equation 30 approximates the joint density of the errors as the product of a squared polynomial and a standardized bivariate normal density where the latter is assumed just for convenience. Gallant and Nychka (1987) demonstrate that 30 approximates densities with arbitrary skewness and kurtosis except those that are violently oscillatory. In implementation, the vector of parameters $\alpha = (\alpha_{00}, \alpha_{01}, ..., \alpha_{r_1 r_2})$ is normalized by setting $\alpha_{00} = 1$ since the polynomial expansion in 30 is invariant to multiplication of the parameter vector by a scalar. The specification of the pseudo–log-likelihood function and the detailed procedures for implementation of the model are explained in De Luca (2008). This approach not only relaxes the parametric assumption of the bivariate probit model in estimating the coefficients but also allows detailed examination of the characteristics of the error densities for different values of $r_1$ and $r_2$.

In addition to the child's height-for-age z scores as a measure of the child's physical fitness, the vector of covariates in all the models includes child's age and gender, number of siblings, livestock and land area owned as measures of the household's wealth status, parents' age and education, as well as distance to a primary school as a proxy for cost of schooling. The indicators for household wealth could be thought of as proxies for household income, discussed in the theoretical model. Information on household income gathered through surveys in the rural areas of developing countries is often unreliable and wealth indicators could be better measures of household well-being. Controlling for wealth indicators is important because the need for child labor and the ability of the families to send their children to school could vary with wealth status. Variation across households and changes over time in wealth indicators could also be correlated with nutritional status of children; thus failing to control for wealth indicators could bias my estimates. The theoretical model described above also implies that the wage rate for child labor is a relevant variable that should be accounted for in the empirical model since the wage paid to a child could be correlated with physical stature. However, child labor in rural Ethiopia almost entirely consists of unpaid family labor, so information on formal wage rates for children is unavailable. The child's opportunity cost of time is essentially his/her marginal product in the family production activity and to the extent that the marginal productivity depends on having other assets to work with, children in the families with more land and livestock could have higher opportunity cost of time than children with less assets. Therefore, inclusion of land and livestock ownership as covariates may partly control for the opportunity cost of the child's time.

The vectors of coefficients from the bivariate probit models are used to calculate the marginal effects of the covariates on the probability of observing each of the joint outcomes: $p(s_i=0, w_i=0)$, $p(s_i=0, w_i=1)$, $p(s_i=1, w_i=0)$, and $p(s_i=1, w_i=1)$. For the purpose of comparison with other studies that estimated an independent equation just for schooling, I also estimate the standard probit models for the child's school attendance and participation in family work. Therefore, the marginal effects of the covariates on $p(s_i=1)$ and $p(w_i=1)$ are computed using both the joint models as well as independent probit models. As briefly described in the previous section, the marginal effect of my key variable of interest, child's physical stature on child schooling and child labor is theoretically ambiguous. The existing literature generally argues that better physical fitness enhances the chances that a child attends schooling implying that its effect on $p(s_i=1)$ will be strongly positive. The effects of physical fitness on the joint outcomes have not been examined by the existing studies. Therefore, the estimates here help us to answer an important question of whether child's physical fitness enhances the child's chances of being a full time student, $p(s_i=1, w_i=0)$, or part-time student, $p(s_i=1, w_i=1)$, or even full-time worker, $p(s_i=0, w_i=1)$.

One important issue that needs to be addressed in estimating these models is the potential endogeneity of the child's physical stature in both schooling and child labor equations. Endogeneity could arise because parents may be providing preferential treatment in terms of nutrition to some children (particularly when resources are limited) in anticipation of specific role for each child depending on their perceptions regarding the importance of physical fitness for each of the child's anticipated roles. For example, parents may feed the oldest child very well so that he/she quickly grows up and helps them in fulfilling the family labor needs. If this is the case it may be the anticipated role for the child (schooling or labor) that is determining his physical stature rather than the other way round and the estimates may not represent a causal effect. Therefore, an exogenous source of variation in nutrition status that is beyond the control of the parents is needed to identify its effects on schooling and child labor. Exposure to a famine caused by a massive drought and localized rainfall shocks are used as identifying instruments as discussed in the next section.

Another critical issue is how to implement instrumental variables estimation in the context of these heavily nonlinear models for non-binary outcomes. There are at least three approaches that have been used to address this issue in various contexts. One possibility is to jointly estimate the first stage equation for the endogenous variable and the second-stage equation for the outcome variable of interest, for example, using the full information maximum likelihood approach to obtain asymptotically efficient estimators as initially proposed by Hausman (1975) . However, the application of this method generally depends on some arbitrary assumptions about the joint distribution of the errors in the two equations the validity of which cannot be readily verified.

The other commonly applied method is what may be called 'two-stage predictor substitution' (2SPS) where the endogenous regressor in the second-stage equation is replaced by its predicted value from a separately run auxiliary regression correcting the standard errors for the resulting measurement error bias (for some of the recent applications of this method see Lu and McGuire 2002; Meer and Rosen 2004; Savage and Wright 2003; Gramm 2003). Unlike the linear models where the two-stage predictor substitution leads to consistent estimates, however, the consistency of such estimates in the non-linear context has not been well established. In fact Terza, Basu and Rathouz (2008) show that such a method generally leads to inconsistent estimates in the non-linear models. On the other hand, they demonstrate that an alternative method that requires inclusion of the residual from the first-stage auxiliary regression in the second-stage equation provides consistent estimates. The two-stage residual inclusion (2SRI) method has been recently used by a number of empirical studies (see Stuart, Doshi, and Terza 2009; Shea et al. 2007; Gibson et al. 2006; Shin and Moon 2007; DeSimone 2002; Baser et al. 2004) but its theoretical properties in such applications have not been formally examined until the latest work by Terza, Basu and Rathouz (2008).

According to Terza, Basu and Rathouz (2008) the 2SRI method provides consistent estimates because the unobserved factors that led to endogeneity of the regressor can be controlled for by the residuals from the first stage auxiliary regression as long as we can find valid identifying instruments. This method provides not only consistent estimates but asymptotically correct standard errors. They test their theoretical results about the consistency of the 2SRI and inconsistency of 2SPS estimates using simulated data with 5,000 and 20,000 observations. They find negligible biases in the 2SRI estimates and several times larger biases in the 2SPS estimates for a duration model with multinomial endogenous treatments and ordered logit model with count-valued endogenous treatments. They apply the two methods to actual data as well and find that the 2SPS method substantially overestimates the effect of the endogenous variable. Therefore, I use the 2SRI method to address the potential endogeneity of the child's physical stature in the bivariate probit models for child labor and schooling where the first stage is a linear model for the child's height-for-age z scores. The two-stage approach fits the models here conceptually as well because parental decisions are formulated as sequential where the early period focuses on building the physical fitness of the child through nutrition and health services and the subsequent period largely focuses on allocating the child's time to schooling or family labor or both.

### 3.1 Identification Strategy

The findings in the literature on nutrition indicate that there is strong relationship between height-for-age in early childhood and height-for-age later in life (e.g., See Martorell et al. 1995; Martorell 1999, 1997). In fact Martorell et al. conclude that "regardless of the choice of reference population, growth is markedly retarded only in early childhood; adolescence is not a period when growth is significantly constrained" (p.1060S). This implies that factors that significantly affect the child's nutritional status during early childhood are likely to be strongly correlated with the child's cumulative nutrition outcome, say height-for-age, later in life. Therefore, if one could find exogenous shocks that could substantially influence the child's nutrition during early childhood, these shocks must be correlated with the child's cumulative nutrition outcomes later in life and hence can be used to identify the effect of the latter on other outcomes for the child like schooling and child labor. Using contemporaneous shocks in such contexts may not be appropriate because they may influence the schooling and child labor outcomes directly, for example by putting the household under resource pressure. On the other hand shocks that happened well in the past are less likely to be directly correlated with current child labor and schooling outcomes except through their long-lasting effect on the child's physical and cognitive abilities.

The fact that the livelihoods of the rural communities in Ethiopia are highly dependent on rainfall conditions provides an opportunity to use rainfall related shocks to identify the effects of early childhood malnutrition on child outcomes later in life. Two approaches are followed in using the rainfall related shocks for this purpose. First, an attempt is made to exploit a famine caused by a massive drought in 1984 where the average rainfall nationwide was 22% below the long-term average, making it the worst drought since rainfall data started to be systematically recorded in 1961 (Webb, von Joachim and Yohannes 1992). While household level data on experience during the famine are largely unavailable, in 1995 a sample of 1477 households from 15 different sites in the country were asked to recall the three biggest droughts over the previous 20 years in which they lost a substantial amount of their harvest and/or livestock. Nearly half the households reported to have lost substantial crop harvest and/or livestock because of the drought in 1984/85 agricultural seasons. The ages of the children in these sample households could be traced back to the time of the drought to identify the group of children who were particularly vulnerable (1 to 3 years old according to the literature on nutrition). These potentially affected children would have been 10 to 12 years old in 1994.

The interactions between dummy variables that identify these children and a dummy variable that identifies households who reported to have faced a substantial shock at the time are used as the first set of identifying instruments for early childhood malnutrition. That is, the identifying instruments are generated by interacting a dummy for the reported household level shock with a dummy for being age 1, a dummy for being age 2 and a dummy for being age 3 in

1984. Children who were 4 to 6 years old at the time of the drought (13 to 15 years old in 1994) are included as controls. These are children who must have been less vulnerable at the time of the drought and must have not sustained substantial damage in their physical stature from the shock.[3] Because of the observed linearity in the relationship between height-for-age in early childhood and later in life (Martorell et al. 1995), the age-shock interactions correlated with height-for-age in the early childhood period should be correlated with height-for-age in 1994 and the subsequent periods. To control for the genetic variation in height I also include the mother's and father's height as additional covariates in the first stage regressions for child's height-for age.[4] This approach is implemented using data from the first round of the Ethiopian Rural Household Survey (ERHS) conducted in 1994 and another round in 1995.

In the absence of detailed data on household experience at the time of the drought, however, the famine shock may still be an imperfect way to accurately identify the degree of malnutrition faced by children from different households. This is so because the capabilities of the households to cope with crop and livestock loss might differ. Another issue with using the famine shocks to identify the effects of malnutrition is that children who survived the famine and are found alive in 1994 could be the stronger ones who could withstand the effects of the drought, while weaker children might have already died, in which case the effect of the shock could be understated.[5] Another concern with this approach is that parents' age recalls may entail some errors in a situation where formal records of child's birth date are not kept, as is largely true in rural Ethiopia. This may be a more serious problem particularly when age recalling involves longer time periods.

As a way of validating the results from the 1984-drought based identification strategy, therefore, an alternative strategy based on localized rain-fall shocks is implemented using data from a different cohort of children who were 1 to 6 years old at the time of the first round of the survey in 1994. The fact that the birth dates for these children are relatively close to the survey period is expected to make it easier for the parents to accurately recall the child's age and hence minimize the potential age-recall error bias. The localized rainfall shocks are defined on the basis of the deviations of the annual rainfall in the locality from its long-term mean.[6] Both substantial rain deficits and excessive rains are considered rainfall shocks since both can lead to crop failure. Substantial rain deficit is represented by a dummy that takes a value of 1 if the rainfall shortfall from the long-term mean is bigger than 1 standard deviation and excessive rainfall shock is represented by a dummy taking a value of 1 if the excess of rain over the long-term mean exceeds 1 standard deviation. Because of the erratic nature of rainfall in most localities in Ethiopia, the long-term standard deviations of rainfall are quite large representing more than 15% of the mean annual rainfall on average. Therefore, rainfall deficits and excesses exceeding 1 standard deviation represent substantial shock that may lead to crop failures and significant reductions in consumption in rural Ethiopia. For example, Dercon (2002) finds that a 10%

[3] Children who were born at and after 1984 may not be an effective comparison group because they may also have been the victims of the after-effects of the drought at their critical age. These children, therefore, are excluded from the sample.

[4] Mother's height was used for similar purpose by Glewwe and Jacoby (1995).

[5] But the data on mortality history gathered during the 1995 round of the survey don't show any unusually high mortality in 1984 for the age group included in our sample.

[6] A similar strategy was followed by Maccini and Yang (2009).

decrease in rainfall from the long-term mean decreases food consumption by up to 5% and localized rainfall shortfalls of this magnitude or bigger are quite common in Ethiopia.

Therefore, the rainfall shocks faced by a child during the first 3 years of life are taken as exogenous indicators of early childhood malnutrition and hence used as instruments for the child's age-standardized heights in the child labor and schooling models. In this case height-for-age measured towards the end of the preschool period is used since the anthropometric data were gathered for all members of the sample households in 1994, 1995 and 1997. The genetic variations in children's height are controlled for by mother's and father's heights in this approach as well. Malnutrition induced by exogenous rainfall shocks is expected to explain what is left of these natural differences in the heights of children. The schooling and child labor models for this cohort of children are estimated using data from the latest two rounds of the survey conducted in 1999 and 2004. The age range for this cohort in 2004 is similar to the age range for the older cohort in 1994. Therefore, results from the two identification strategies are expected to be at least qualitatively comparable although rainfall shortfalls might be weaker instruments than the major famine shock.

## 4. Data and Summary Statistics

The analysis in this paper is based on data from the various rounds of the Ethiopian rural household survey (ERHS) conducted by the Economics Department of Addis Ababa University in collaboration with the Center for the Study of African Economies at the University of Oxford, the International Food Policy Research Institute (IFPRI) and the US Agency for International Development (USAID). ERHS is a unique longitudinal data set in Ethiopia the first round of which was conducted in 1994 (subsequently referred to as 1994a) and covered 1477 households from 15 different sites across the country. Another round was conducted later in 1994 (henceforth referred to as 1994b) followed by one round each in 1995, 1997, 1999 and 2004. The attrition rate was small between successive rounds and the 6$^{th}$ round in 2004 managed to successfully re-interview about 1370 of the households in the original sample. The 15 sites (called peasant associations) were selected to represent the major farming systems[7] in the county and households were randomly selected from the list of households in each peasant association. While strictly speaking ERHS is not nationally representative[8], the major statistics from this survey are very close to those from nationally representative surveys (see Dercon 2000).

All the rounds of the ERHS data contain detailed information on household demographics, asset ownership, as well as income and consumption. Information on height and weight for all household members was gathered in all the rounds except in 1999. The anthropometric data in the ERHS are directly collected by the enumerators using measuring scales. While this may not totally eliminate measurement errors, it is expected to minimize it compared to the surveys where data on respondent heights and weights are collected through self-reporting. Information on exposure to significant drought shocks was gathered during the 1995 round. In this round households were asked to list three most important droughts (listed in the order of severity) over the last 20 years because of which they suffered substantial loss of harvest and/or livestock.

[7] These are the grain-plough areas of the Northern and Central highlands, the Enset-growing areas and the sorghum-hoe areas.

[8] The pastoralist farming system was not represented,

The analysis that uses the 1984 drought as exogenous source of malnutrition focuses on the cohort of children who were 10 to 15 years old during the 1994a round (henceforth called the older cohort) who must have been 1 to 6 years old during the 1984 drought. Those who were age 1 to 3 may be considered as the treatment group because this is the age range that evidence from the nutrition literature shows is the critical period where malnutrition can have a lasting impact on the child's stature. Those who were 4 to 6 could be considered as the comparison group because there is not strong evidence that malnutrition beyond age 3 has a lasting impact on the child's physical stature. For the analysis where localized rainfall shocks are used as exogenous sources of malnutrition data from the cohort of children who were 1 to 6 years old during 1994a round (henceforth called the younger cohort) are used.

Data on child activities were collected in 1994a, 1995, 1999 and 2004. Child activity data for the analysis involving the older cohort comes from 1994a and 1995 rounds. However, the level of detail in the data on child-activity was different in the two rounds. In 1994a, data on child activities were collected as part of main activities for all household members and the main activity categories for children included student, farm worker, domestic worker, domestic and farm worker, off-farm business worker, and not involved in work[9]. This round did not ask questions on activity combinations of children. On the other hand the 1995 round collected data on not only the main activity of the child but also on secondary and tertiary activities. Specifically, the 1995 round asked the 1$^{st}$, 2$^{nd}$ and 3$^{rd}$ activity of the child ranked in terms of hours spent on each. These activity combinations were collected for both students and non-students. As a result, it is possible to identify children who combined schooling and child labor in 1995 but not in 1994a. Child activity data for the analysis involving the younger cohort comes from the 1999 and the 2004 rounds. Both rounds collected data on both main and secondary activities of all household members including children out of which data on activity combinations for children in the sample cohort are compiled.

Height-for-age z-scores for children were calculated using the software, ANTHRO[10], which uses in-built median heights and weights for similar age groups and gender from the healthy U.S. population as references. The age-standardized height for each child thus represents the number of standard deviations by which the child's height deviates from the median height of the healthy U.S. children with similar age and gender. For the older cohort age-for-height z-scores from 1994a and 1995 rounds are used. An ideal data for the purpose at hand would have been to use height-for-age data collected after the critical period (age 3) but before the school age[11] since the height of the child in this period will fully reflect the outcome of his/her early childhood nutrition experience. Unfortunately, such data are unavailable for the older cohort but the analysis based on child heights measured in 1994 and 1995 but identified through a malnutrition shock experienced during the early childhood period will still be informative

[9] While some of the activities such as farming could vary seasonally, most of the activities in which children participate like herding cattle, fetching water and fuel wood, watching the little kids and other domestic chores are year round activities and there will always be something for children to do throughout the year. Therefore, seasonality is assumed away in our analysis.
[10] The software is provided by WHO and is available at http://www.who.int/childgrowth/software/en/index.html, last accessed April, 2009.

[11] While there is no official school starting age in Ethiopia, it is rare for a child in rural Ethiopia to start school before age 7 because of the long distances children have to travel to get to the nearest elementary school.

because of the observed linear relationship between height-for-age at the end of the critical period and height-for-age later in life.

On the other hand, data on the preschool height and weight are available for the younger cohort. Therefore, the analysis involving data from the younger cohort uses child height-for-age measured after the critical period but before the school age. For those who were 4 to 6 years old during 1994a, height data reported in 1994a or 1994b (if height is missing in 1994a) are taken. For those who were 3 years old during 1994a, height data reported in 1995 round are taken while for those who were 1 or 2 years old during 1994a, height data reported in 1997 are taken. Therefore, estimation results from the younger cohort are expected to directly reflect the effects of early childhood malnutrition on the child activity choices.

The monthly data on rainfall for the stations closest to the survey sites were obtained from the Ethiopian Meteorological Agency for the period from 1970 to 2006. The key rainfall data needed for the purpose at hand were for the 8 years or 96 months from 1988-1995 for each of the 15 sites when the children in the younger cohort were at their critical stage of development[12]. From the total of these1440 key monthly rainfall records, however, 249 were missing [13](see tables B1&B2 in appendix B for details) and replaced by the long-term average for the same month from the same station. The annual rainfall data were then obtained by adding up the monthly data for each year. Annual rainfall deviations for each locality were calculated by subtracting the long-term mean rainfall for the locality from the annual rainfall. Then, three variables representing rainfall deviation that prevailed during the 1st, 2nd and 3rd years of each child in the younger cohort were defined. Three dummies identifying substantial rain-deficit during the 1st, 2nd and 3rd years of the child are then defined to take a value of 1 if the absolute value of the rain shortfall for the respective year was greater than 1 long-term standard deviation for the rainfall in the locality. Three other dummies identifying excessive rain during 1st, 2nd, and 3rd years are also defined to take a value of 1 if the excess of the rainfall over the long-term mean the child faced during the respective year was greater than 1 standard deviation. These six dummies represent the local rainfall shocks[14] that children in the younger cohort experienced during the critical period of their development.

In addition to the child's height-for-age z-scores, a number of control variables are included in the estimated econometric models reported in the next section. These include land

[12] For those who were 1 year old during 1994a round the critical years were taken to be 1993, 1994 and 1995. For those who were 2 years old the critical years were 1992, 1993 and 1994. For the 3 year olds the critical years were 1991, 1992 and 1993. For the 4 year olds the critical years were 1990, 1991 and 1992. For the 5 year olds the critical years are 1989, 1990 and 1991. For the 6 year olds the critical years are 1988, 1989 and 1990.

[13] While these are a lot of missing data by any standard and could possibly lead to understatement of the effects of the rainfall shocks, our results remain nearly unchanged when we re-estimate our models for the younger cohort by excluding all the major cases with missing rainfall data as we report in the next section. Glewwe and King (2001) also used rainfall data with large number of missing observations as an instrument for child malnutrition in Philippines and pointed out that the instrument could have understated the effects of child malnutrition on cognitive development.

[14] The identification strategy based on the localized rainfall shocks assumes that the households lived at their current site for at least the first 6 years of the child's life. According to the data collected on the migration history of the household head and his/her spouse during the 1994b round, the household head was either born in the survey site or arrived before 13 years except 2 cases where the head arrived before 7 years and 5 years. Therefore, mobility doesn't seem to be an issue in our sample.

and livestock ownership as well as the distance to the nearest primary school. Data on agricultural land area owned by the household were collected in local units that varied across survey sites. The land areas measured in local units were converted into hectares using the land conversion units gathered through the community questionnaire of the ERHS. The various types of livestock owned were also converted into equivalent units and aggregated using the tropical livestock equivalent units that are available in the 1999 round of the survey. Data on distance to the nearest primary school were gathered only in the 1997 and 2004 rounds. Therefore, the distances to primary schools for the 1994a and 1995 rounds are approximated by the distances observed in 1997. The distances to primary schools in 1999 were also approximated by the distances observed in 1997 except when the data gathered in 2004 indicated that a closer school was constructed between 1997 and 1999 in which case the distance information for 1999 were updated to the latest.

The summary statistics for child activities and the covariates used in the first and second stages of the econometric models for the older cohort are presented in table A1 in appendix A. In the sample of households interviewed for the 1994a round, there are 1232 children of the older cohort with complete information for the variables of interest. About 24% were students whereas 69% were participating in family labor activities full-time. About 7% were neither working nor attending school. For this round we do not have information as to who among the students were combining work with schooling. On the other hand, 1116 children of the older cohort have information for the variables of interest in the data for the 1995 round out of whom 25% were full time students and 9% were combining schooling and family work. The proportion of students is 10 percentage points higher during the 1995 round. The rapid change may have to do with the aggressive primary school expansion program initiated by the new government at the time. We observe similarly rapid growth in the percentage of students between 1999 and 2004 for the younger cohort.

The average height-for-age z-score for the older cohort is -1.96 during the 1994a round and -2.12 during the 1995 round. This means that children in this cohort are about 2 standard deviations shorter on average than the healthy American children of the same age. According to the WHO standards[15], children with height-for-age z-score less than -2.00 are considered stunted (display retarded growth). About half (49% in 1994a and 53% in 1995) of the children in this cohort were stunted. The evidence in table 1A also shows that about 60% of the children in this cohort belonged to households that lost substantial amount of crops and/or livestock because of the 1984 drought out of which well over one half were at the critical age (age 1 to 3) at the time of the drought. There are also some indications that those who were affected by the drought at their critical age were more stunted than children of the same age who were not affected by the drought. According to the height measurements from the 1994a round for example, children affected by the drought at their critical age had average height-for-age of -1.93 compared to -1.75 for children of the same age who were not affected by the drought. The pattern is similar in 1995 as well although the difference is smaller in the latter case and the standard errors are a bit large in both cases perhaps because of small sample sizes for each category. The first stages of the econometric models reported in the next section formally estimate the effect of the drought on height-for-age z-scores.

[15] See the WHO growth standards at http://www.who.int/childgrowth/standards/en/, accessed April, 2010.

The summary statistics for the variables used in the econometric models for the younger cohort are presented in table A2 in appendix A. Out of the 1184 children in this cohort with complete data for all the variables of interest during the 1999 round, 14% were full-time students while 18% were combining schooling and family work for a total of 32% participation in schooling. About 21% were neither working nor attending school while 48% were full-time participants in family activities. In 2004 there were 1057 children of this cohort with complete information of which 70% were students (13% attending fulltime and 57% combining schooling and work). Again we observe rapid increase in school participation between 1999 and 2004.

The average pre-school height-for-age z-score for the younger cohort was about -2.2 indicating that stunting of children in Ethiopia is not limited to children who suffered under unusual environmental shocks but rather a widespread phenomenon that afflicts children of all ages. In fact, about 59% of the children in this cohort were stunted during the preschool period and one of the principal causes of stunting is early childhood malnutrition. And malnutrition in most localities in Ethiopia is caused by rainfall fluctuations and the resulting crop failure and livestock death. The large average standard deviation reported for annual rainfall in table A2 is indicative of the degree of unpredictability of rainfall in some of the regions covered by the ERHS survey. Because of this unpredictability at least some of the children born in any given year are likely to face some major crop failure in their locality during their critical years.

The evidence in table A2 shows that a sizable proportion of the children in the younger cohort faced substantial rainfall deficits and/or excessive rains during their first, second or third years. About 12%, 16% and 19% experienced substantial rain deficits in their $1^{st}$, $2^{nd}$ and $3^{rd}$ years, respectively. On the other hand, 13%, 11% and 9% experienced excessive rains during their $1^{st}$, $2^{nd}$ and $3^{rd}$ years, respectively. Both substantial rain shortages and excessive rains are considered a shock because farmers develop their cropping patterns on the basis of their expectations about rainfall in their locality that is often based on their individual and collective experience over so many years. Therefore, any variation in rainfall that falls within its long-term standard deviation will generally be anticipated by the farmers but rainfall deficits and surpluses exceeding the long-term standard deviation will be unanticipated and are likely to lead to crop failures. The effects of these early childhood rainfall shocks on the cumulative nutritional health of the children are estimated in the first stage of the econometric models for the younger cohort.

## 5. Estimation Results

In this section the estimated econometric models of child labor and schooling are presented for both the older and the younger cohorts. To address the potential endogeneity of height-for-age in the schooling and child labor equations I estimate the models in two-stages the validity of which is previously discussed. In the first stage I regress the height-for-age z-scores of the children on the instruments and the other covariates in the second stage of the corresponding equation using the same sample observations. The first stage results are interesting in themselves because they show how weather shocks experienced early in life influence the subsequent physical stature of the child. In the next section, therefore, I briefly present the first stage results for the models reported later in this section.

### 5.1 First Stage Results

The first stage for each model estimated in two-stages is an OLS regression of the height-for-age z-scores on the relevant instruments and other covariates in the model. For the older cohort, the instruments are generated by interacting the dummy identifying the drought-affected children with three age dummies identifying those children who were at the critical stage of development at the time of the 1984 drought. The drought dummy itself is also included to see if the height-for-age was systematically different for drought affected children of all ages (not just those in the critical stage). The three age dummies are also included to see if height-for-age is systematically different for those who were at the critical stage in 1984 (not just those who were affected by drought). In addition, we include the mother's and father's height to control for the genetic variation in children's height so that the malnutrition caused by the drought explains only what is left of the natural differences in the heights of the children.

The procedure I followed in the case of the younger cohort is slightly different because of the way the rainfall shocks at the critical ages are defined. For the older cohort I essentially treated those who were age 4-6 and those who were at the critical stage but unaffected by the 1984 drought as comparison groups and those who were affected by the 1984 drought at the critical age as the treatment group. For the younger cohort as well the treatment comes from a rainfall shock experienced during the critical ages but the time at which they experienced the shock varies depending on their age and locality. Therefore, I don't have specific shock-period and age-cohort dummies to control for. The control group here as well consists of those who did not experience substantial rainfall shock during their critical years. Like the case with the older cohort I include mother's and father's height to control for the genetic variation in the heights of children. The first stage results for both cohorts are presented in table A3 in appendix A.

The first three columns in table A3 present the first stage results for the models estimated using data from the older cohort while the last two columns present the first stage results of the models for the younger cohort. All the first stage equations were estimated using OLS, correcting the standard errors for the household level clustering. Equations I and III are similar except that equation I includes year dummy for the survey round. Equations IV and V are also the same except that the former includes year dummy for the survey round. The year dummy is included in all the models estimated using the pooled panel data in an attempt to control for the potential confounding effects of the time-varying unobserved characteristics of the family and the child.

The set of instruments defined on the basis of exposure to the 1984 drought for the older cohort and localized rainfall shocks for the younger cohort are jointly significant in the first stage equations and generally have anticipated signs. In the results for the older cohort we have consistently negative signs for a big drought experienced during the 1$^{st}$, and 2$^{nd}$ years while the signs for the 3$^{rd}$ year are mixed. For the younger cohort we have consistent negative signs for excessive rains experienced during the 1$^{st}$ ,2$^{nd}$ and 3$^{rd}$ years and substantial rain deficits during the 2$^{nd}$ and 3$^{rd}$ years. The sign for substantial rain deficit during the 1$^{st}$ year is positive but small compared to the other coefficients. In the results for the older cohort it is important to note that the drought dummy itself has in fact a positive sign implying children who belonged to the drought affected families in general had in fact bigger average height-for-age z-scores than those who belonged to the non-affected families. Therefore, isolating the effect of the drought on the group at the critical age was important for identification of its effect because that is where the negative effect is visible (as also suggested by the nutrition literature).

One remarkable observation about these first stage results is the fact that weather shocks appear to have their strongest effect on the child's physical stature during the second[16] year of his/her life for both the older and the younger cohorts. I find that both the 1984 drought and substantial localized rain shortages have large and statistically significant negative effects on the child's subsequent height-for-age when experienced during the 2nd year. According to these results being exposed to a significant drought during the second year reduces height-for-age z-scores of children by more than 0.5 points on average which represents about 25% of the mean height-for-age for this group of children. The effect of substantial rainfall deficit during the second year is somewhat similar (0.4 points or about 18% of the mean height-for-age z score for the younger cohort). Even the excessive rain has relatively larger negative effect during the 2nd year although it is not statistically significant at the conventional levels with a t-ratio of 1.26. In the case of the older cohort this large negative effect of drought during the 2nd year is observed despite the fact that second year olds in general had higher average height-for-age z-scores as demonstrated by the positive coefficient on the dummy for age-2 in 1984. This evidence supports the hypothesis that unavailability of additional food for the child will be more detrimental to the child's growth in the second 2nd year than the 1st because of the increasing inadequacy of breast-feeding as a source of nutrition for the child.

### 5.2 Main Results and Discussion

This section presents estimation results for the econometric models of child activity choice described in the section on econometric models and estimation methodology. Two sets of results are obtained for each of the bivariate probit, and probit models for child activity choices. First, each model is estimated through the standard maximum likelihood method, ignoring the potential endogeneity of the child's height-for-age. Second, all the models are re-estimated in two stages (using the procedure previously described) so as to address the potential endogeneity of my key variable of interest. In each case the standard errors are corrected for household level clustering.

For the older cohort the bivariate probit models with four child activity classifications ($s_i=0, w_i=0; s_i=0, w_i=1; s_i=1, w_i=0;$ and $s_i=1, w_i=1$) are estimated using cross sectional data only from the 1995 round because the 1994a round did not collect data on child activity combinations. On the other hand, the probit models for child schooling are estimated using pooled panel from both rounds since data on schooling are available in both rounds. For the younger cohort all the models for child activity choices are estimated using pooled panel (unbalanced) data from the 1999 and 2004 rounds. All the models estimated with pooled panel data include year dummies intended to control for the possible over-time variation in the un-observed child and family characteristics. In addition, the probit models for schooling are estimated with random effects to see if controlling for unobserved family and child heterogeneities substantially alters the results.

The coefficient estimates for the bivariate probit models for child activity choices are presented in table A4 in appendix A. For the probit models the coefficient estimates are presented in table A9 in appendix A. However, joint estimation of child schooling and child labor equations as bivariate probit seems to be more appropriate as demonstrated by the highly

[16] Alderman et al for Zimbabwe and Glewwe and King (2001) for Philippines find similar results.

significant correlation between the errors in the schooling and child labor equations reported in table A4. Therefore, my discussion of the results mainly focuses on the estimates from bivariate probit model although the key results for the probit models are also reported for comparison.

The magnitudes of the coefficient estimates for the types of non-linear models reported here are not very informative in themselves. From the results obtained for each model therefore, I have calculated the marginal effects of my key variable of interest, child's height-for-age, on activity choices at each value of the regressor keeping the values of the other covariates at their mean values. Following the standard practice in the literature I focus on the discussion of the marginal effects of height-for-age at the mean but also present the average marginal effects.

The marginal effects at the mean of height-for-age obtained from all the models for the older cohort and the younger cohort are presented in table 1 and table 2 below, respectively. The average marginal effects of height-for-age on activity choices are reported in tables A6 and A7 in appendix A for the Older and Younger cohorts, respectively. The marginal effects of height-for-age obtained from probit models for participation in family work activities are also reported in these tables[17].

One general pattern we observe in these results is that the absolute magnitudes of the estimates are much larger in the two-stage models in all the cases perhaps implying that failing to address the endogeneity of child's height-for-age could substantially understate its estimated effect on the child's participation in schooling and family labor activities[18]. On the other hand, the two-stage estimates generally have bigger standard errors leading to lack of (or less) statistical significance for some of the marginal effects obtained from the two stage models, particularly for the older cohort. Another notable pattern in these results is the general similarity in the signs and magnitudes of the estimated partial effects for the younger and the older cohort. The fact that we find generally similar results for two different cohorts is somewhat remarkable given the differences in sources of identification and the time periods at which children's heights were measured for the two cohorts.

Table 1. Marginal effects (at the mean value) of Child's Height-for-age z-scores on the Choice Probabilities of Various Child Activities (Older Cohort)

| Model | p(stud=1\|x) | p(stud=1, work=0\|x) | p(stud=1, work=1\|x) | p(stud=0, work=1\|x) | p(stud=0, work=0\|x) | p(work=1\|x) |
|---|---|---|---|---|---|---|
| Biprobit | 0.043*** | -0.001 | 0.044*** | -0.040*** | -0.003** | 0.004 |
| | (0.012) | (0.006) | (0.011) | (0.011) | (0.002) | (0.007) |
| Biprobit, two-stage | 0.071 | -0.004 | 0.075 | -0.065 | -0.006 | 0.010 |
| | (0.080) | (0.035) | (0.066) | (0.079) | (0.007) | (0.041) |
| Probit | 0.041*** | - | - | - | - | 0.007 |
| | (0.008) | | | | | (0.006) |
| Probit, two-stage | 0.090** | - | - | - | - | 0.007 |
| | (0.054) | | | | | (0.041) |

17 The coefficient estimates for these models are not reported but available from the author upon request.

18 Alderman et al. (2001) find similar disparity between simple probit estimates and two-stage probit estimates of the effect of child's height-for-age on school enrollment in rural Pakistan.

| | | | | | | |
|---|---|---|---|---|---|---|
| RE probit | 0.040*** | - | - | - | - | - |
| | (0.009) | | | | | |
| RE prob., two-Stage | 0.064 | - | - | - | - | - |
| | (0.058) | | | | | |

***p<0.01, ** p<0.05, *p<0.1

Notes: Tables A4 and A5 in appendix A respectively present coefficient estimates for bivariate probit and Probit results from which these partial effects were obtained. The partial effects reported in this table are the averages of partial effects calculated at each value of the child's height-for-age z- scores and the standard errors were calculated by the delta method. All models included controls for community fixed effects, child age and sex, land and livestock owned, household size and number of siblings, education of father and mother, distance to primary school, age of mother and father, and sex of household head.

The results for both the older cohort (in Table 1) and the younger cohort (in Table 2) confirm the findings in the earlier studies that access to better nutrition during early childhood enhances the child's chances of attending school later in life. This is true both in the joint models for child labor and schooling as well as the separate probit models for just child schooling (see 1st columns in tables 1 and 2). Focusing on the two-stage bivariate probit estimates, reducing the gap between the height-for-age of the sample in the older cohort and healthy American children with the same age by 1 standard deviation will increase the probability of school attendance by the former by 7.1%. For the younger cohort the corresponding estimate is 10%. Given the average height-for-age z scores of about -2, these estimates would mean that eliminating this height deficit through better nutrition and care in the early childhood would boost the chances of attending school by about 14.1% for the older cohort and by about 20% for the younger cohort. The signs and statistical significances of the estimated marginal effects of height-for-age on schooling obtained from the probit models are similar to the estimates from bivariate probit models but slightly different in magnitudes. Although some of the estimated marginal effects are not statistically significant at the conventional levels of significance, it is important to note that the standard errors obtained through the delta method are generally noisy and may not be as informative[19] as the signs and magnitudes of the estimates.

Table 2. Marginal effects (at the mean value) of Child's Height-for-age z-scores on the Choice Probabilities of Various Child Activities (Younger Cohort)

| Model | p(stud=1\|x) | p(stud=1, work=0\|x) | p(stud=1, work=1\|x) | p(stud=0, work=1\|x) | p(stud=0, work=0\|x) | p(work=1\|x) |
|---|---|---|---|---|---|---|
| Biprobit | 0.034*** | 0.004 | 0.030*** | -0.026*** | -0.008*** | 0.004 |
| | (0.007) | (0.004) | (0.006) | (0.007) | (0.002) | (0.005) |
| Biprobit, two-stage | 0.100*** | -0.013 | 0.113*** | -0.064* | -0.036*** | 0.048 |
| | (0.038) | (0.023) | (0.032) | (0.035) | (0.012) | (0.031) |
| Probit | 0.034*** | - | - | - | - | 0.002 |
| | (0.007) | | | | | (0.004) |
| Probit, two-stage | 0.097** | - | - | - | - | 0.043 |
| | (0.039) | | | | | (0.031) |
| RE probit | 0.042*** | - | - | - | - | 0.002 |

[19] That is partly why we present the plots of the entire distributions of some of the marginal effects later in this section.

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.008) | | | | | (0.005) |
| RE prob., two-stage | 0.119** | - | - | - | - | 0.043 |
| | (0.048) | | | | | (0.028) |

***p<0.01, ** p<0.05, *p<0.1

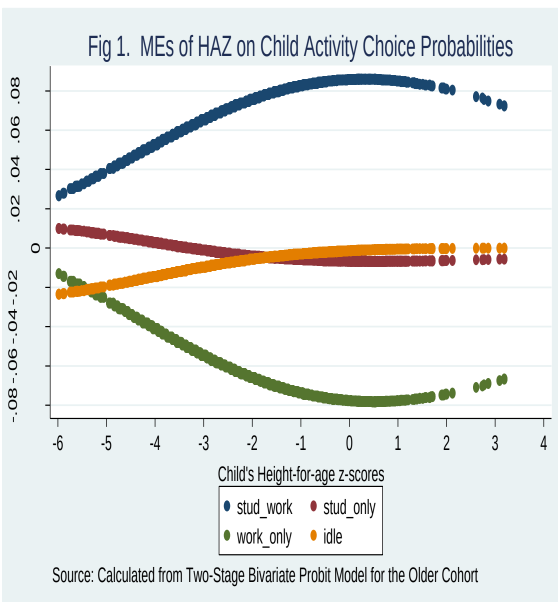
Notes: Tables A4 and A5 in appendix A respectively present coefficient estimates for bivariate probit and Probit results from which these partial effects were obtained. The partial effects reported in this table are the averages of partial effects calculated at each value of the child's height-for-age z- scores and the standard errors were calculated by the delta method. All models included controls for community fixed effects, child age and sex, land and livestock owned, household size and number of siblings, education of father and mother, distance to primary school, age of mother and father, and sex of household head.

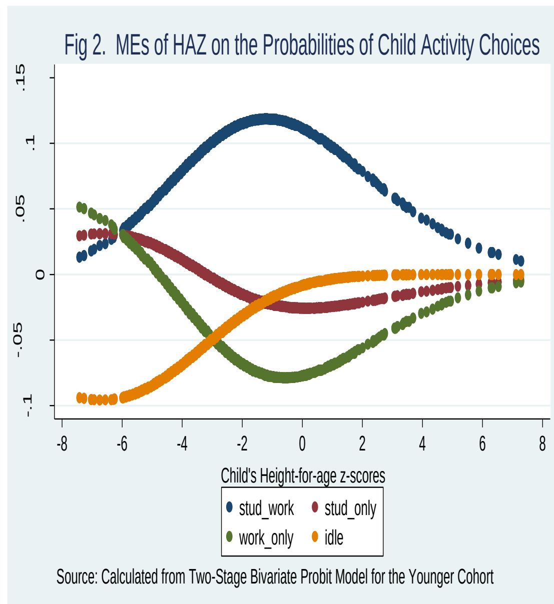
While the marginal effects at the mean of the child's height-for-age on his/her participation in family labor activities are also positive as shown along the last columns of tables 1 and 2, these effects are generally small in magnitude and mostly insignificant. This is so because about 89% of the children in the pooled sample for the younger cohort and 95% of the pooled sample for the older cohort were participating in family labor activities. Therefore, a more meaningful estimate would be the partial effect of the child's height-for-age on the probabilities of being selected for full-time family labor, $p(s=0, w=1|x)$. These estimates are obtained from bivariate probit model and are reported along the 4$^{th}$ columns of the tables for the marginal effects. The results show that the marginal effect of child's height-for-age on the probability of being selected for full-time family labor is consistently negative except at the extremely low values of height-for-age z-scores for the younger cohort (see fig 2 below). However, the two-stage versions of these estimates are statistically insignificant for the older cohort and mostly insignificant for the younger cohort. Based on this evidence, therefore, I find no support for the hypothesis that physically stronger children will be positively selected for full time family labor.

On the other hand, the estimates reported along the 3$^{rd}$ columns of the tables for the marginal effects consistently show that the physically stronger children are more likely to combine schooling and family labor than the physically less fit children. The marginal effects at mean as well as the average marginal effects of height-for-age on the probability of combining schooling and work, $p(s=1,w=1|x)$, is consistently positive and much bigger than its marginal effects on all the other choices for child activities for both the older and the younger cohort.

In contrast, both the marginal effects at mean and average marginal effects of height-for-age on the probability of being selected for full-time schooling , $p(s=1,w=0|x)$, are either negative or positive but close to zero as shown along the 2$^{nd}$ columns of the tables for the marginal effects. In addition, the marginal effects on the probability of being selected for full time schooling in the two-stage models are rarely significant while the marginal effects on combining schooling and family labor are either significant at conventional levels or generally have standard errors smaller than the estimated partial effects. Therefore, there appears to be reasonably strong and consistent evidence that better physical stature enhances the probability that the child is asked to participate in family activities while attending school but no evidence that better physical fitness increases the chances of being selected for either fulltime schooling or fulltime family labor. It is important to note that better physical fitness seems to reduce the probability that the child remains idle, $p(s=0, w=0|x)$, although the marginal effects of height-for-age on this choice are small in magnitude particularly for the older cohort. The bottom line from these results is that, a point increase in the height-for-age z-score of the child will substantially increase the probability of combining schooling and family labor, will reduce the probability of being selected for full-time family labor, but will have little effect on the probabilities of being selected for full-time schooling or being idle.

My discussion so far was based on the marginal effects at the mean and the average marginal effects but this may not be fully informative if the marginal effects considerably vary at different values of height-for-age. To check whether the aforementioned relationships between the marginal effects of height-for-age on various child activity choices hold at points other than the mean, I plot[20] the marginal effects against the values of height-for-age z-scores for my preferred two-stage bivariate probit model. Fig 1 and Fig 2 below present these plots for the older and younger cohorts, respectively.

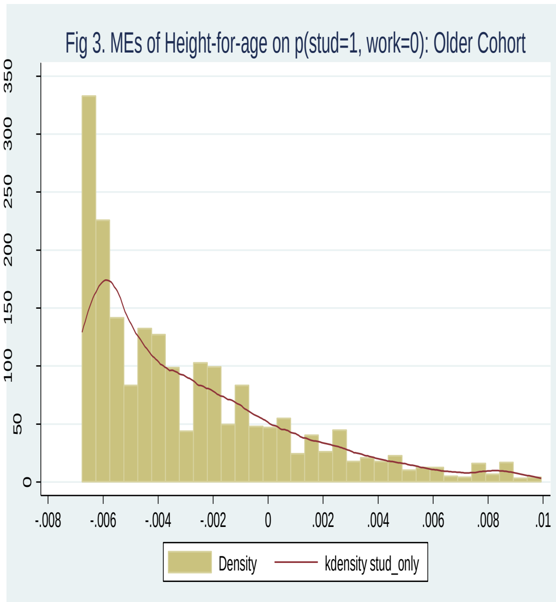


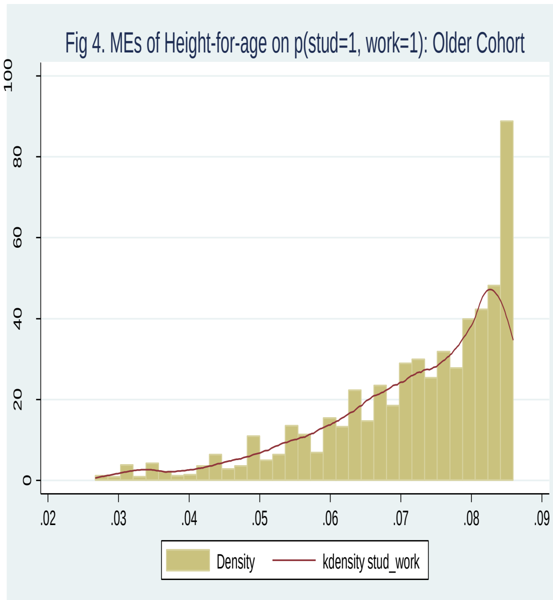




Although the observed range of values for height-for-age z-scores vary for the younger and older cohorts (-5.98 to 3.19 for the older cohort and -7.41 to 7.28 for the younger cohort), Fig 1 and Fig 2 show somewhat remarkable similarity in the patterns of the marginal effects for the comparable ranges of values of height-for-age. The marginal effects of height-for-age on the probability of combining schooling and work (stud_work) remain positive and much bigger than the marginal effects on the probabilities of being selected for other activity categories at all values of height-for-age except at the extremes. On the other hand the marginal effects on the probability of being selected for the full-time schooling (stud_only) remain close to zero for both cohorts while the marginal effects on the probability of being selected for full-time family work

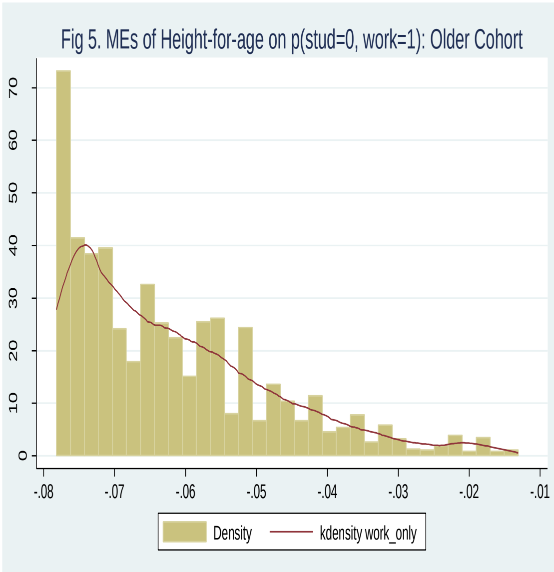
[20] While this shows how the marginal effect on the probability of each activity choice varies with changing values of height-for-age, the calculation of marginal effects at each point assumes linearity and the possible non-linearity in the effects of height-for-age on child activity choice is not addressed here. Inclusion of quadratic terms in our models doesn't seem to be informative because of the negative observations on height-for-age z-scores. An alternative way could be to estimate the models for various ranges of values for height-for-age and compare the resulting marginal effects. This is also infeasible in our case because of small sample size we are working with but future studies can address the issue using data from a larger sample.

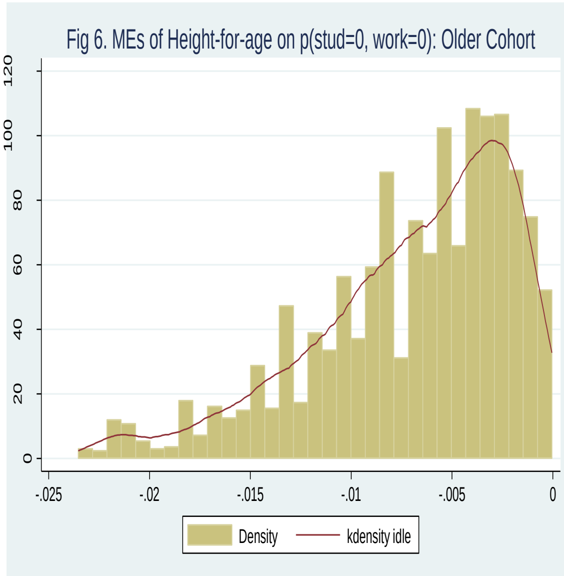
(work_only) remain mostly negative. The patterns in the marginal effects of height-for-age on the probability of being idle appear to differ for the two cohorts at smaller values of height-for-age but the overall pattern is similar here as well. Therefore, the relationship between the marginal effects we observed at the mean of height-for-age is not limited to that particular point but holds throughout except at the extremes where we have only a few observations and hence all the marginal effects approach zero. In fact my conclusion based on the marginal effects at the mean or the average marginal effects seems to be reasonable since most of the marginal effects are clustered around the marginal effects at the mean as demonstrated by their Epanechnikov kernel densities[21] presented in Figs 3-6 for the older cohort and Figs 7-10 for the younger cohort.



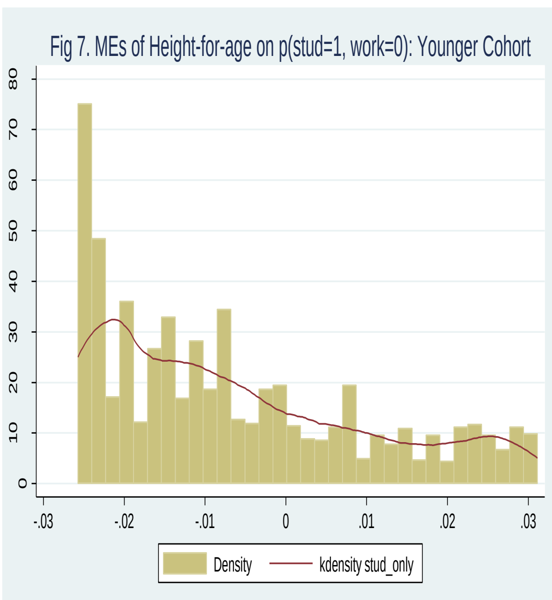



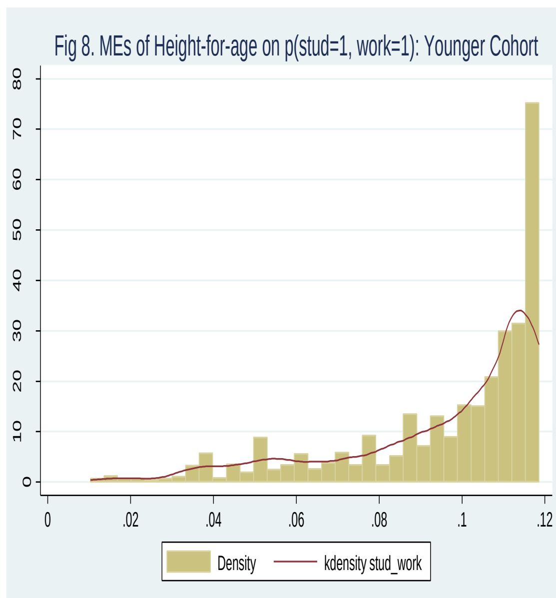

[21] The "optimal" width is used in constructing each of the kernel densities for the MEs. The optimal width is the width that would minimize the mean integrated squared error.

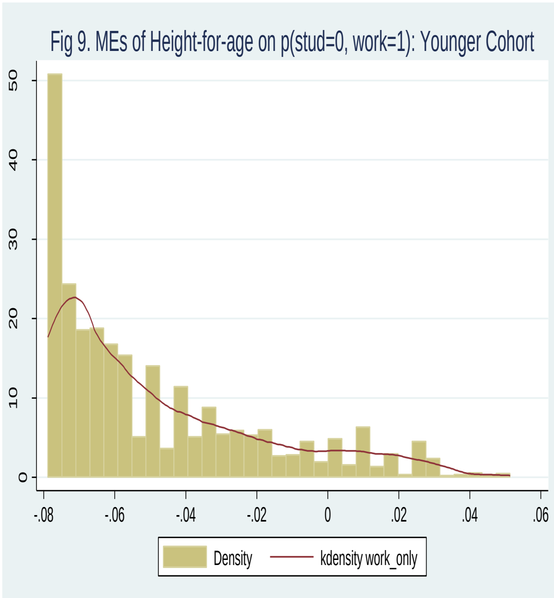


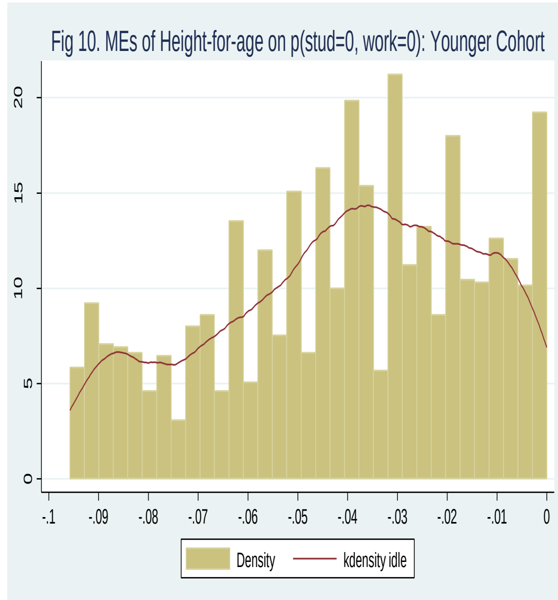




Source: Calculated from Two-Stage Bivariate Probit Model for Schooling and Work for the Older Cohort.
Notes: MEs stands for marginal effects and p stands for probability.





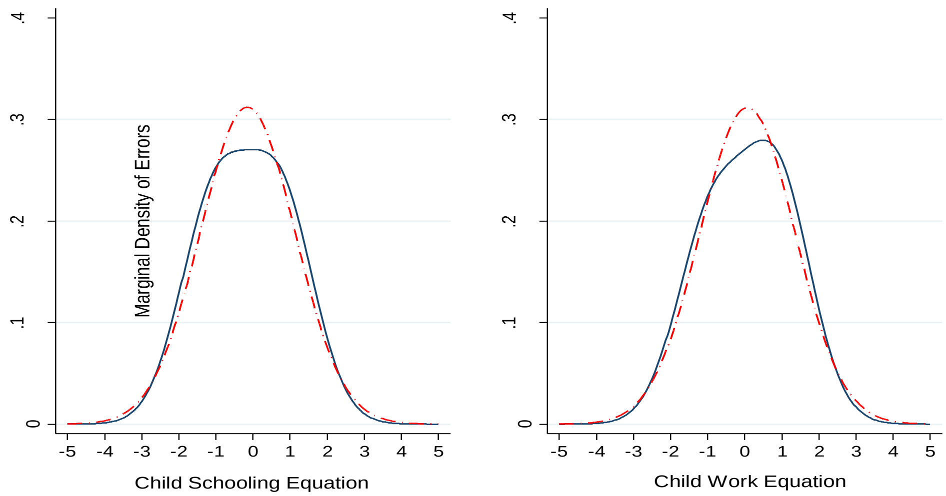




Source: Calculated from Two-Stage Bivariate Probit Model for Schooling and Work for the Younger Cohort.
Notes: MEs stands for marginal effects and p stands for probability.

With the exception of the kernel densities of marginal effects of height-for-age on the probability of being idle that are based on relatively smaller number of observations (Fig 6 for the older cohort and Fig 10 for the younger cohort), all the other kernel densities are clearly uni-modal and highly skewed with the bulk of the marginal effects clustered around the marginal effect at the mean that itself is close to the mode of the distribution in each case. For example, the marginal effect at the mean of height-for-age on the probability of combining schooling and family work is 0.075 for the older cohort and 0.113 for the younger cohort in the two-stage bivariate probit models as shown in tables 1 and 2, respectively. The corresponding average marginal effects are 0.062 and 0.08 as shown in tables A6 and A7 in Appendix A for the older and younger cohorts, respectively. The mode of the distribution for the corresponding marginal effects is about 0.085 for the older cohort (Fig 4) and about 0.118 for the younger cohort (Fig 8) around which the bulk of the marginal effects are lumped. The same is more or less true for the marginal effects of height-for-age on the probabilities of being selected for full time schooling and full-time family labor. That is why the average marginal effects reported in tables A6 and A7 in appendix A and the marginal effects at the mean are not very far apart. Hence, the conclusions I arrived at on the basis of the marginal effects at the mean of height-for-age seem to be reasonable.

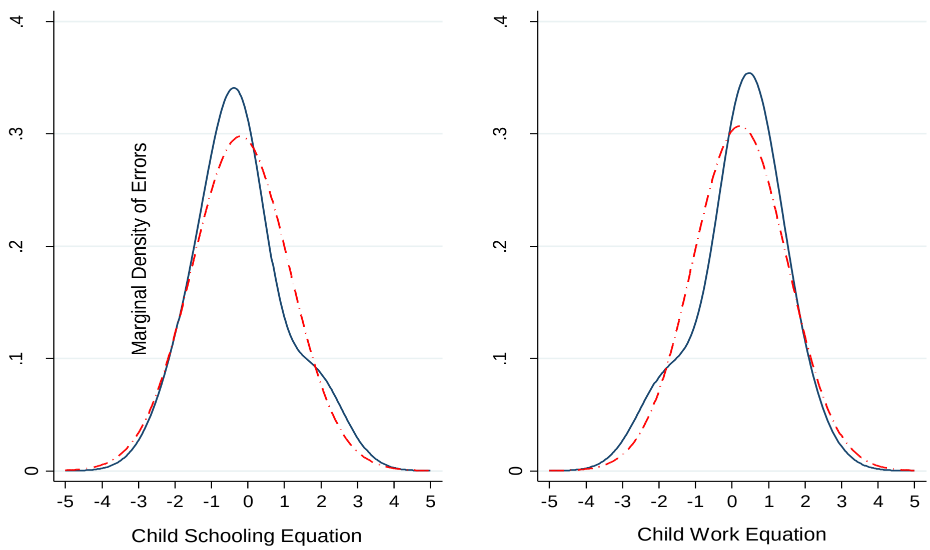
To get some feel about the validity of the bivariate probit parametric form for the joint distribution of the errors in the schooling and work equations, I tried to re-estimate the bivariate models following Gallant and Nychka's (1987) semi-nonparametric approach previously described. Strict application of their approach requires estimating the models for successively increasing order of the Hermite polynomial and testing the superiority of a lower order against higher order using likelihood-ratio tests or by model-selection criteria such as the Akaike information criterion or the Bayesian information criterion. With the relatively small sample of observations, however, I could hardly obtain convergence for the non-concave pseudo–log-likelihood function with Hermite polynomials of more than 2 degrees. For the older cohort the pseudo–log-likelihood function for the two stage model failed to converge even when I set the order of the polynomial at 2 for both schooling and work equations but it converged when I set either $r_1$ or $r_2$ to 1. Fig 11 depicts the error densities from the two stage model for the older cohort when $r_1$=2 and $r_2$=1 while Fig 12 presents the error densities from the two-stage model for the younger cohort when the order of the Hermite polynomial for both equations is set to 2. The detailed characteristics of these densities along with the estimated coefficients for the covariates are presented in table A8 in appendix A.

Fig 11. Error Densities from Semi-nonparametric Estimation (2-Stage, Older Cohort)




Note: The Order of Hermite Polynomials was 2 for Schooling and 1 for Work.

Fig 12. Error Densities from Semi-nonparametric Estimation (2-Stage,Younger Cohort)




Note: The Order of Hermite Polynomials was 2 for both Schooling and Work Equations.

In the cases where convergence was obtained, the error densities are symmetric and do not seem to substantially deviate from a normal distribution (in reds) with similar first and second moments as demonstrated in Fig 11 and Fig 12 for the older and the younger cohorts, respectively. The measures of skewness and kurtosis reported in table A8 in appendix A are consistent with this observation. Although the magnitudes of the coefficient estimates from the semi-nonparametric models are not directly comparable to those from the bivariate probit model since the former depend on the normalization of the coefficients of the Hermite polynomials, the signs and statistical significances of the coefficients are generally consistent with the exception of the two-stage equation for the child work for the older cohort. Given the symmetry of the error densities and qualitative resemblance in the estimated coefficients, therefore, the bivariate probit model doesn't seem to be unreasonable for my data.

Finally, I tried to check if my results for the younger cohort are being driven by the replacement of the missing monthly rainfall records with their long-term averages by re-estimating the models for the younger cohort, successively excluding the major cases with missing rainfall records from my estimation sample. The results from this exercise for my preferred bivariate probit model are reported in table B3 in appendix B. The corresponding first-stage results and marginal effects are reported in tables B4 and B5, respectively. The first adjustment I make is to limit my estimation sample to those who had at least 6 months of non-missing rainfall records including the main rainy (agricultural) season in the locality for at least 1 of the three critical years of development. The next adjustment I make is to limit my estimation sample to those who fulfill the same condition as in the first adjustment for at least 2 of the three critical years of development. And finally I limit my estimation sample to those who fulfill the same condition for all the three critical years of development. These adjustments produce little changes in the signs, magnitudes and qualities of the first-stage results, the coefficient estimates and the corresponding marginal effects as shown in the appendix. For example, I lose 283 observations because of the final adjustment but the marginal effect at the mean of height-for-age on p(stud=1, work=1) decreases from 0.113 to 0.106, its marginal effect on p(stud=1, work=0) decreases from -0.013 to -0.016, the marginal effect on p(stud=0, work=1) increases from -0.064 to -0.055 and the marginal effect on p(stud=0, work=0) increases from -0.038 to -0.036. While I still kept some cases with smaller number of missing rainfall records in my estimation sample, if there was a major understatement of my estimates because of the missing rainfall records it is likely that larger changes in the estimates would have been observed when I removed all the major cases with missing rainfall records. Hence, it doesn't seem that my results for the younger cohort are being driven by the replacement of the missing rainfall records by their long-term averages.

In general, therefore, the findings from both the older and younger cohort indicate that better access to early childhood nutrition can improve the child's prospects for attending schooling but may also put the child in additional pressure to participate in family labor activities. This may take the form of asking the child to miss classes in order to help with family labor activities at home, for example, when agricultural activities are at their peak during harvesting season or the child may be asked to look after the livestock or fetch drinking water or fuel wood after coming back from school or during the weekends. While the data at hand do not contain information on the child's performance at school and hence do not allow analysis of how performance may be affected by the child's physical stature, it is quite possible that the additional pressure put on the child's time from the family labor activities could constrain the amount of time the child could spend on home works and other school related activities at home and hence lead to poor performance at school. Therefore, policies that try to promote schooling through nutrition support programs could be more effective if they are accompanied by programs (such as income support schemes) that could mitigate the forces that push families to resort to child labor.

## 6. Conclusion

This paper examines how malnutrition experienced during early childhood influences the subsequent participation of the child in schooling and child labor activities in rural Ethiopia. The cumulative outcome of the child's early childhood nutritional experience is measured by the child's height-for-age z-score which is also taken as a measure of the child's physical fitness. My theoretical model implies that the effect of the child's physical fitness on the parental choice as to whether to select the child for schooling or child labor is ambiguous. Bivariate probit as well as separate probit models are estimated to empirically examine the effect of the child's physical fitness on his/her participation in schooling and family labor activities. Data from various rounds of a unique longitudinal rural household survey in Ethiopia (Ethiopian Rural Household Survey) are used to estimate the models. To address the potential endogeneity of the child's physical fitness in the models for child activity choices, I estimate the models in two-stages. Exposure to a famine caused by a massive drought in 1984 is used as an exogenous source of early childhood malnutrition for the older cohort of children for whom the models were estimated. Localized rainfall shocks were used as a source of identification for the younger cohort of children for whom a separate set of estimates were obtained.

The first stage results show that exposure to significant weather shocks during the first three years of the child's life generally have a lasting negative effect on his/her age standardized heights measured later in life. The effect is particularly strong when the child is exposed to the shock during his/her second year. Estimation results from the child's activity choice models indicate that better early childhood nutrition enhances the child's chances of attending school later in the child's life. The range of marginal effects obtained from the two stage bivariate probit models imply that equalizing the median height of the children in the sample for the two cohorts with the heights of healthy American children of the same age through better nutrition and care in the early childhood would boost the chances of school attendance among the children by at least 14% and possibly by as much as 20%.

On the other hand, I find no conclusive evidence that better physical fitness of the child leads to his/her positive selection for full-time child labor activities. I rather found reasonably strong and consistent evidence that physically robust children are more likely to combine child labor and schooling than physically weaker children. The results are consistent across two different cohorts of children and two different identification strategies. The findings indicate that, although better early childhood nutrition leads to higher chances of attending school, it may also put the child at additional pressure to participate in family labor activities and this may be reflected in poor performance in schooling. Therefore, policies that try to promote schooling through nutrition support programs could be more effective if they are accompanied by programs that could mitigate the forces that push families to resort to child labor. My next work in this area will look at how the observed effect of physical fitness on the probability of combining child labor and schooling affects the child's school performance in the form of test scores and grades.

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## APPENDICES

### Appendix A. Summary Statistics and Additional Results

Table A1. Summary Statistics for the Variables Used in the Econometric Models for the Older Cohort

| | | 1994a (Obs=1232) | | 1995 (Obs=1116) | |
|---|---|---|---|---|---|
| Variable | Description | Mean | St.dev | Mean | St.dev |
| Student | dummy=1 if student at school | 0.24 | 0.43 | 0.34 | 0.48 |
| Working | dummy=1 if working | | | 0.89 | 0.31 |
| Neither a student nor working | dummy=1 if neither student at school nor working | 0.07 | 0.26 | 0.02 | 0.13 |
| Student Only | dummy=1 if student at school and not working | | | 0.09 | 0.29 |
| Work only | dummy=1 if working and not student at school | 0.69 | 0.46 | 0.64 | 0.48 |
| Student and working | dummy=1 if student at school and working | | | 0.25 | 0.44 |
| Child activity | activity=0 if idle, =1 if student only , =2 if work only, =3 if student and working | | | 2.13 | 0.63 |
| Main activity of child | main activity=0 if idle, =1 if student, =2 if working | 1.61 | 0.62 | 1.62 | 0.51 |
| Sex | sex=1 if male | 0.51 | 0.50 | 0.51 | 0.50 |
| Age | Age | 12.40 | 1.76 | 13.10 | 1.63 |
| Agri. land area owned | Agricultural land area owned | 1.87 | 1.76 | 2.12 | 2.15 |
| Livestock units owned | Tropical livestock units owned | 4.89 | 6.68 | 4.77 | 6.35 |
| Father's education | dummy=1 if child's father has completed at least primary education | 0.08 | 0.27 | 0.08 | 0.28 |
| Mother's education | dummy=1 if child's mother has completed at least primary education | 0.02 | 0.14 | 0.02 | 0.13 |
| Distance to primary school | Distance to the nearest primary school in kilometers | 6.00 | 4.27 | 6.16 | 4.40 |
| Household size | Household Size | 8.26 | 3.24 | 8.73 | 3.39 |
| Number of siblings | Number of siblings of the child | 5.04 | 2.85 | 5.28 | 2.93 |
| Age of father | Age of child's father | 49.30 | 9.82 | 49.93 | 9.93 |
| Age of mother | Age of child's mother | 40.05 | 8.43 | 40.81 | 8.61 |
| Sex of household head | dummy=1 if h.hold head is male | 0.82 | 0.39 | 0.81 | 0.39 |
| Drought Affected in 1984 | dummy=1 if household lost crop and/or livestock because of 1984 | | | | |

| | | | | | |
|---|---|---|---|---|---|
| | drought | 0.60 | 0.49 | 0.62 | 0.48 |
| First Year in 1984 | dummy=1 if child was in his/her first year in 1984 | 0.20 | 0.40 | 0.23 | 0.42 |
| Second Year in 1984 | dummy=1 if child was in his/her second year in 1984 | 0.14 | 0.35 | 0.17 | 0.37 |
| Third Year in 1984 | dummy=1 if child was in his/her third year in 1984 | 0.19 | 0.39 | 0.21 | 0.41 |
| Drought Affected at 1st Year | dummy=1 if child was in 1st year IN 1984 and belonged to drought affected household | 0.12 | 0.32 | 0.14 | 0.35 |
| Drought Affected at 2nd Year | dummy=1 if child was in 2nd year in 1984 and belonged to drought affected household | 0.09 | 0.28 | 0.11 | 0.31 |
| Drought Affected at 3rd Year | dummy=1 if child was in 3nd year in 1984 and belonged to drought affected household | 0.12 | 0.33 | 0.14 | 0.34 |
| Height-for-age | Child's Height-for-age z-scores | -1.96 | 1.54 | -2.12 | 1.44 |
| Height-for-age(Dr84) | Obs.94=742, Obs.95 =697 | -1.99 | 1.52 | -2.11 | 1.47 |
| Height-for-age (No Dr84) | Obs.94=490, Obs.95 =419 | -1.91 | 1.55 | -2.15 | 1.38 |
| Height-for-age(Dr84, A1-3) | Obs.94=406, Obs.95 =426 | -1.93 | 1.60 | -2.05 | 1.48 |
| Height-for-age (No Dr84, A1-3 ) | Obs.94=259, Obs.95 =249 | -1.75 | 1.61 | -1.98 | 1.39 |
| Height-for-age(Dr84, A4-6) | Obs.94=336, Obs.95 =271 | -2.07 | 1.44 | -2.21 | 1.65 |
| Height-for-age (No Dr84, A4-6 ) | Obs.94=231, Obs.95 =170 | -2.09 | 1.42 | -2.39 | 1.35 |
| Height of mother | Height of mother in centimeters | 156.7 | 7.31 | 156.8 | 5.71 |
| Height of father | Height of father in centimeters | 168.2 | 5.35 | 165.9 | 7.84 |

Source: Ethiopian Rural Household Survey.
Notes: Dr84 identifies children affected by the 1984 drought; A1-3 identifies children who were 1 to 3 years old at the time of the 1984 drought while A4-6 identifies children who were age 4 to 6 at the time; Obs.94/Obs.95 stand for the number of observations in the category during the 1994a/1995 rounds.

Table A2. Summary Statistics for the Variables Used in the Econometric Models for the Younger Cohort

| | | 1999 (Obs=1184) | | 2004 (Obs=1057) | |
|---|---|---|---|---|---|
| Variable | Description | Mean | St.dev | Mean | St.dev. |
| Student | dummy=1 if student at school | 0.32 | 0.47 | 0.70 | 0.46 |
| Student Only | dummy=1 if student at school and not working | 0.14 | 0.35 | 0.13 | 0.33 |
| Working | dummy=1 if working | 0.65 | 0.48 | 0.86 | 0.34 |
| Work only | dummy=1 if working and not student at school | 0.48 | 0.50 | 0.29 | 0.45 |
| Student and working | dummy=1 if student at school and working | 0.17 | 0.38 | 0.57 | 0.49 |

| | | | | | |
|---|---|---|---|---|---|
| Neither student nor working | dummy=1 if neither student at school nor working | 0.21 | 0.40 | 0.01 | 0.12 |
| Main activity of child | main activity=0 if idle, =1 if student, =2 if working | 1.27 | 0.78 | 1.28 | 0.48 |
| Child activity | activity=0 if idle, =1 if student only, =3 if work only,=3 if student and working | 1.62 | 1.00 | 2.42 | 0.76 |
| Child's Height-for-age | Child's Height-for-age z-scores | -2.22 | 2.06 | -2.25 | 2.04 |
| Sex | sex=1 if male | 0.50 | 0.50 | 0.52 | 0.50 |
| Age | Age | 8.24 | 1.77 | 13.24 | 1.77 |
| Household size | Household Size | 8.83 | 3.49 | 7.20 | 2.35 |
| Number of siblings | Number of siblings of the child | 4.45 | 2.08 | 4.66 | 2.14 |
| Sex of household head | dummy=1 if h.hold head is male | 0.81 | 0.39 | 0.79 | 0.41 |
| Father's education | dummy=1 if child's father has completed at least primary education | 0.17 | 0.38 | 0.18 | 0.38 |
| Mother's education | dummy=1 if child's mother has completed at least primary education | 0.05 | 0.22 | 0.06 | 0.23 |
| Distance to primary school | Distance to the nearest primary school in kilometers | 4.69 | 3.67 | 3.74 | 3.04 |
| Age of father | Age of child's father | 47.96 | 10.97 | 52.81 | 11.01 |
| Age of mother | Age of child's mother | 37.92 | 8.42 | 42.80 | 8.32 |
| Agri. Land area owned | Agricultural land area owned | 1.46 | 1.40 | 1.44 | 1.70 |
| Livestock units owned | Tropical livestock units owned | 4.08 | 4.03 | 6.21 | 7.57 |
| Rainfall deviation at 1st year | Deviation of rain from long run local mean during 1st year | 21.89 | 171.13 | 22.50 | 172.69 |
| Rainfall deviation at 2nd year | Deviation of rain from long run local mean during 2nd year | -3.66 | 160.23 | -2.51 | 152.11 |
| Rainfall deviation at 3rd year | Deviation of rain from long run local mean during 3rd year | -23.58 | 169.76 | -21.53 | 164.68 |
| Substantial rain def. at 1st year | dummy=1 if rain deficit at 1st year exceeds local st.dev | 0.13 | 0.33 | 0.12 | 0.32 |
| Substantial rain def. at 2nd year | dummy=1 if rain deficit at 2nd year exceeds local st.dev | 0.17 | 0.38 | 0.16 | 0.37 |
| Substantial rain def. at 3rd year | dummy=1 if rain deficit at 3rd year exceeds local st.dev | 0.20 | 0.40 | 0.19 | 0.39 |
| Substantial rain sur. at 1st year | dummy=1 if rain surplus at 1st year exceeds local st.dev | 0.13 | 0.33 | 0.13 | 0.33 |
| Substantial rain sur. at 2nd year | dummy=1 if rain surplus at 2nd year exceeds local st.dev | 0.12 | 0.32 | 0.11 | 0.32 |
| Substantial rain sur. at 3rd year | dummy=1 if rain surplus at 3rd year exceeds local st.dev | 0.09 | 0.28 | 0.09 | 0.29 |

| | | | | | |
|---|---|---|---|---|---|
| Height of mother | Height of mother in centimeters | 156.57 | 6.44 | 156.45 | 6.56 |
| Height of father | Height of father in centimeters | 166.23 | 7.90 | 166.20 | 7.80 |

Source: Ethiopian Meteorological agency for the rainfall data, Ethiopian Rural Household Survey for all the Other Variables.

Table A3. The Effect of Exposure to Drought and Rainfall Fluctuations in Early Childhood on Height-for-age Z- scores (First Stage Results)

| | **Older Cohort** | | | **Younger Cohort** | |
|---|---|---|---|---|---|
| | I | II | III | IV | V |
| | (94a&95) | (1995) | (94a&95) | (99&04) | (99&04) |
| Drought Affected in 1984 | 0.171 | 0.294* | 0.170 | | |
| | (0.151) | (0.173) | (0.151) | | |
| First Year in 1984 | 0.129 | 0.242 | -0.058 | | |
| | (0.303) | (0.366) | (0.228) | | |
| Second Year in 1984 | 0.462* | 0.431 | 0.322 | | |
| | (0.261) | (0.311) | (0.214) | | |
| Third Year in 1984 | -0.202 | -0.106 | -0.294* | | |
| | (0.199) | (0.224) | (0.171) | | |
| Drought Affected at 1st Year | -0.094 | -0.077 | -0.094 | | |
| | (0.202) | (0.216) | (0.201) | | |
| Drought Affected at 2nd Year | -0.592*** | -0.487** | -0.590*** | | |
| | (0.227) | (0.246) | (0.227) | | |
| Drought Affected at 3rd Year | 0.098 | -0.055 | 0.098 | | |
| | (0.193) | (0.207) | (0.193) | | |
| Substantial rain def. at 1st year | | | | 0.047 | 0.061 |
| | | | | (0.223) | (0.220) |
| Substantial rain def. at 2nd year | | | | -0.401** | -0.402** |
| | | | | (0.179) | (0.180) |
| Substantial rain. def. at 3rd year | | | | -0.243 | -0.237 |
| | | | | (0.178) | (0.178) |
| Substantial rain surp. at 1st year | | | | -0.030 | -0.034 |
| | | | | (0.178) | (0.178) |
| Substantial rain surp. at 2nd year | | | | -0.227 | -0.221 |
| | | | | (0.180) | (0.179) |
| Substantial rain surp. at 3rd year | | | | -0.094 | -0.085 |
| | | | | (0.251) | (0.250) |
| Height of Mother | 0.023*** | 0.024*** | 0.023*** | 0.028*** | 0.028*** |
| | (0.007) | (0.009) | (0.007) | (0.010) | (0.010) |
| Height of Father | 0.006 | 0.006 | 0.007 | 0.027*** | 0.027*** |
| | (0.006) | (0.008) | (0.006) | (0.008) | (0.008) |
| Age | -0.078 | -0.059 | -0.125*** | -0.020 | -0.007 |
| | (0.063) | (0.083) | (0.041) | (0.032) | (0.017) |
| Sex | -0.229*** | -0.171** | -0.230*** | -0.223* | -0.222* |
| | (0.075) | (0.081) | (0.074) | (0.119) | (0.118) |
| Household Size | -0.034 | -0.023 | -0.033 | 0.016 | 0.012 |
| | (0.022) | (0.023) | (0.022) | (0.025) | (0.024) |
| Number of Siblings | 0.053** | 0.040 | 0.052** | -0.034 | -0.030 |
| | (0.024) | (0.025) | (0.024) | (0.035) | (0.035) |
| Sex of Household Head | -0.032 | -0.026 | -0.033 | -0.102 | -0.102 |
| | (0.133) | (0.152) | (0.133) | (0.157) | (0.157) |

| | | | | | |
|---|---|---|---|---|---|
| Father's Education | 0.346* | 0.369** | 0.338* | 0.200 | 0.203 |
| | (0.181) | (0.181) | (0.181) | (0.188) | (0.188) |
| Mother's Education | -0.060 | -0.164 | -0.064 | -0.343 | -0.340 |
| | (0.439) | (0.491) | (0.438) | (0.260) | (0.260) |
| Age of Father | 0.004 | 0.006 | 0.004 | 0.004 | 0.005 |
| | (0.005) | (0.006) | (0.005) | (0.008) | (0.008) |
| Age of Mother | 0.022*** | 0.020*** | 0.022*** | 0.009 | 0.009 |
| | (0.006) | (0.007) | (0.006) | (0.011) | (0.011) |
| Agri. Land Area Owned | 0.005 | 0.021 | 0.003 | 0.003 | 0.003 |
| | (0.024) | (0.029) | (0.023) | (0.032) | (0.032) |
| Livestock Units Owned | 0.003 | -0.002 | 0.003 | -0.011 | -0.010 |
| | (0.007) | (0.008) | (0.007) | (0.010) | (0.010) |
| Year=1995 | -0.103 | | | | |
| | (0.069) | | | | |
| Year=2004 | | | | 0.108 | |
| | | | | (0.167) | |
| Constant | -6.894*** | -7.488*** | -6.365*** | -11.453*** | -11.535*** |
| | (1.739) | (2.149) | (1.663) | (1.901) | (1.873) |
| F-stat for joint sig of instruments | 2.900*** | 2.470*** | 2.910*** | 7.620*** | 7.610*** |
| | (p=0.005) | (p=0.008) | (p=0.002) | (p=0.000) | (p=0.000) |
| Observations | 2348 | 1116 | 2348 | 2241 | 2241 |

Cluster-robust standard errors in parentheses

*** p<0.01, ** p<0.05, *p<0.1

Notes: Site dummies were included in all the equations as controls for community fixed effects. Equation I presents the first stage for the probit models estimated using pooled unbalanced panel data from 1994a and 1995 rounds. Equation II presents the first stage results for the bivariate probit models estimated using cross-sectional data from 1995 round. Equation III presents the first stage results for the random effects probit models estimated using unbalanced panel data from 1994a and 1995 rounds. Equation IV is the first stage for all the models estimated using pooled panel data for the younger cohort whereas equation V is the first stage for the random effects probit models for the same cohort. All first stage equations were separately estimated by OLS and the resulting residuals were used in the second stage equations as suggested by Terza, Basu and Rathouz (2008).

Table A4. Bivariate Probit Estimates for Child Schooling and Work

| | Older Cohort | | Younger Cohort | |
|---|---|---|---|---|
| | I | II | III | IV |
| | Biprobit | 2-Stage Biprobit | Biprobit | 2-Stage Biprobit |
| **Student** | | | | |
| Child's Height-for-age z-scores | 0.121*** | 0.199 | 0.086*** | 0.251*** |
| | (0.032) | (0.223) | (0.018) | (0.095) |
| Sex | 0.330*** | 0.344*** | 0.284*** | 0.324*** |
| | (0.082) | (0.090) | (0.066) | (0.070) |
| Age | 0.040 | 0.048 | 0.196*** | 0.199*** |
| | (0.025) | (0.034) | (0.018) | (0.018) |
| Agri. Land Area Owned | -0.014 | -0.016 | -0.000 | -0.002 |
| | (0.030) | (0.031) | (0.024) | (0.024) |
| Livestock Units Owned | 0.011 | 0.011 | 0.023*** | 0.024*** |
| | (0.012) | (0.012) | (0.008) | (0.008) |
| Father's Educ.-at Least Primary | 0.855*** | 0.824*** | 0.400*** | 0.349*** |

| | | | | |
|---|---|---|---|---|
| | (0.176) | (0.197) | (0.104) | (0.107) |
| Mother's Educ.-at Least Primary | 0.061 | 0.074 | 0.419*** | 0.472*** |
| | (0.404) | (0.403) | (0.142) | (0.143) |
| Distance to Primary School | 0.034 | 0.033 | -0.027* | -0.027* |
| | (0.026) | (0.026) | (0.016) | (0.016) |
| Household Size | 0.011 | 0.013 | -0.025 | -0.030* |
| | (0.022) | (0.022) | (0.016) | (0.016) |
| Number of Siblings | 0.010 | 0.006 | 0.046** | 0.052** |
| | (0.024) | (0.025) | (0.021) | (0.021) |
| Age of Father | -0.005 | -0.005 | -0.005 | -0.006 |
| | (0.006) | (0.006) | (0.005) | (0.005) |
| Age of Mother | 0.006 | 0.004 | 0.003 | 0.001 |
| | (0.007) | (0.008) | (0.006) | (0.006) |
| Sex of Household Head | -0.005 | -0.007 | 0.109 | 0.113 |
| | (0.136) | (0.136) | (0.095) | (0.094) |
| Year=2004 | | | 0.055 | 0.043 |
| | | | (0.105) | (0.105) |
| Resid. from Height-for-age eqn. | | -0.079 | | -0.169* |
| | | (0.227) | | (0.095) |
| Constant | -1.449** | -1.291* | -2.376*** | -1.892*** |
| | (0.568) | (0.747) | (0.266) | (0.390) |
| **Work** | | | | |
| Child's Height-for-age z-scores | 0.030 | 0.065 | 0.014 | 0.162 |
| | (0.045) | (0.268) | (0.015) | (0.103) |
| Sex | -0.276*** | -0.270** | -0.072 | -0.035 |
| | (0.107) | (0.117) | (0.062) | (0.065) |
| Age | 0.032 | 0.035 | 0.138*** | 0.141*** |
| | (0.032) | (0.042) | (0.018) | (0.018) |
| Agri. Land Area Owned | 0.002 | 0.001 | 0.082** | 0.081** |
| | (0.040) | (0.040) | (0.037) | (0.037) |
| Livestock Units Owned | 0.012 | 0.012 | 0.001 | 0.002 |
| | (0.017) | (0.017) | (0.011) | (0.011) |
| Father's Educ.-at Least Primary | -0.088 | -0.099 | -0.157* | -0.200** |
| | (0.241) | (0.274) | (0.090) | (0.095) |
| Mother's Educ.-at Least Primary | 0.378 | 0.380 | 0.092 | 0.140 |
| | (0.456) | (0.459) | (0.143) | (0.148) |
| Distance to Primary School | -0.012 | -0.012 | 0.041** | 0.041** |
| | (0.033) | (0.033) | (0.021) | (0.021) |
| Household Size | -0.043 | -0.041 | 0.014 | 0.010 |
| | (0.030) | (0.031) | (0.017) | (0.017) |
| Number of Siblings | -0.001 | -0.002 | -0.036 | -0.030 |
| | (0.030) | (0.033) | (0.023) | (0.023) |
| Age of Father | -0.000 | -0.001 | 0.005 | 0.004 |
| | (0.008) | (0.008) | (0.004) | (0.004) |
| Age of Mother | 0.001 | 0.000 | 0.003 | 0.002 |
| | (0.010) | (0.012) | (0.006) | (0.006) |
| Sex of Household Head | 0.238 | 0.237 | 0.025 | 0.025 |
| | (0.164) | (0.164) | (0.099) | (0.099) |
| Year=2004 | | | 0.093 | 0.080 |
| | | | (0.108) | (0.109) |
| Resid. from Height-for-age eqn. | | -0.037 | | -0.152 |

| | | | | |
|---|---|---|---|---|
| | | (0.268) | | (0.105) |
| Constant | 1.207 | 1.273 | -0.897*** | -0.467 |
| | (0.736) | (0.881) | (0.258) | (0.389) |
| Athrho | | | | |
| Constant | -0.964*** | -0.964*** | -0.512*** | -0.521*** |
| | (0.101) | (0.101) | (0.053) | (0.053) |
| Observations | 1116 | 1116 | 2241 | 2241 |

*** p<0.01, ** p<0.05, * p<0.1

Cluster-robust standard errors in parentheses

Notes: Dummies representing exposure to a big drought in 1984 at 1st, 2nd and 3rd years are used as identifying instruments for child's height-for-age in equation (II) . Dummies for substantial rain deficit and rain surplus at 1st, 2nd and 3rd years are used as instruments in (V). Mother's height and father's height were also included in all first stage equations to control for genetic variations in height. Site dummies were included in all equations to control for community fixed effects. The two-stage models are estimated using the approach suggested by Terza, Basu and Rathouz (2008) as previously discussed.

Table A5. Probit Models for Child Schooling

| | Pooled Panel | | Panel | | Pooled Panel | | Panel | |
|---|---|---|---|---|---|---|---|---|
| | I | II | III | IV | V | VI | VII | VII |
| | Probit | 2-Stage Probit | RE Probit | 2-Stage RE Probit | Probit | 2-Stage Probit | RE Probit | 2-Stage RE Probit |
| Child's Height-for-age | 0.125*** | 0.276* | 0.159*** | 0.253 | 0.085*** | 0.242** | 0.105*** | 0.299** |
| | (0.025) | (0.166) | (0.035) | (0.228) | (0.018) | (0.097) | (0.020) | (0.120) |
| Sex | 0.441*** | 0.477*** | 0.664*** | 0.686*** | 0.276*** | 0.314*** | 0.339*** | 0.385*** |
| | (0.068) | (0.078) | (0.107) | (0.120) | (0.066) | (0.070) | (0.080) | (0.085) |
| Age | 0.072*** | 0.087*** | 0.152*** | 0.161*** | 0.201*** | 0.204*** | 0.251*** | 0.252*** |
| | (0.019) | (0.025) | (0.030) | (0.038) | (0.018) | (0.018) | (0.018) | (0.018) |
| Agri. Land Area Owned | 0.003 | 0.002 | 0.027 | 0.027 | -0.001 | -0.002 | -0.001 | -0.002 |
| | (0.025) | (0.025) | (0.033) | (0.033) | (0.024) | (0.024) | (0.035) | (0.035) |
| Livestock Units Owned | 0.007 | 0.006 | 0.009 | 0.009 | 0.022*** | 0.023*** | 0.028*** | 0.029*** |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.007) | (0.008) | (0.009) | (0.009) |
| Father's Education | 0.951*** | 0.898*** | 1.453*** | 1.420*** | 0.415*** | 0.366*** | 0.500*** | 0.440*** |
| | (0.154) | (0.163) | (0.213) | (0.227) | (0.106) | (0.108) | (0.122) | (0.126) |
| Mother's Education | 0.055 | 0.059 | 0.008 | 0.011 | 0.443*** | 0.495*** | 0.524*** | 0.587*** |
| | (0.376) | (0.374) | (0.388) | (0.388) | (0.144) | (0.145) | (0.195) | (0.199) |
| Distance to Primary School | 0.034 | 0.033 | 0.042 | 0.041 | -0.024 | -0.024 | -0.034 | -0.034 |
| | (0.023) | (0.024) | (0.032) | (0.032) | (0.015) | (0.015) | (0.022) | (0.022) |
| Household Size | 0.007 | 0.012 | -0.006 | -0.003 | -0.025 | -0.030* | -0.029 | -0.033* |
| | (0.018) | (0.019) | (0.026) | (0.027) | (0.016) | (0.016) | (0.018) | (0.018) |
| Number of Siblings | 0.014 | 0.005 | 0.041 | 0.036 | 0.048** | 0.053** | 0.057** | 0.063** |
| | (0.020) | (0.022) | (0.028) | (0.030) | (0.021) | (0.021) | (0.025) | (0.026) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Age of Father | -0.002 | -0.003 | -0.002 | -0.002 | -0.005 | -0.006 | -0.007 | -0.008 |
| | (0.005) | (0.005) | (0.007) | (0.007) | (0.005) | (0.005) | (0.005) | (0.005) |
| Age of Mother | 0.003 | 0.000 | 0.005 | 0.003 | 0.004 | 0.002 | 0.005 | 0.003 |
| | (0.005) | (0.007) | (0.008) | (0.009) | (0.006) | (0.006) | (0.007) | (0.007) |
| Sex of Household Head | 0.070 | 0.073 | 0.040 | 0.043 | 0.124 | 0.129 | 0.133 | 0.138 |
| | (0.103) | (0.103) | (0.145) | (0.145) | (0.095) | (0.094) | (0.103) | (0.103) |
| Year=1995 | 0.331*** | 0.345*** | | | | | | |
| | (0.056) | (0.058) | | | | | | |
| Year=2004 | | | | | 0.031 | 0.018 | | |
| | | | | | (0.105) | (0.105) | | |
| Residuals from 1st stage. | | -0.154 | | -0.096 | | -0.161* | | -0.199* |
| | | (0.168) | | (0.230) | | (0.097) | | (0.121) |
| Constant | -2.23*** | -1.91*** | -3.61*** | -3.41*** | -2.46*** | -2.00*** | -3.03*** | -2.45*** |
| | (0.456) | (0.577) | (0.698) | (0.842) | (0.270) | (0.393) | (0.316) | (0.462) |
| lnsig2u | | | 0.224 | 0.223 | | | -0.69*** | -0.70*** |
| | | | (0.190) | (0.190) | | | (0.264) | (0.265) |
| No. of Individuals | | | 1358 | 1358 | | | 1263 | 1263 |
| Observations | 2348 | 2348 | 2348 | 2348 | 2241 | 2241 | 2241 | 2241 |

*** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses

Notes: Dummies representing exposure to a big drought in 1984 at 1st, 2nd and 3rd years are used as identifying instruments for child's height-for-age in (II) &(IV) . Dummies for substantial rain deficit and rain surplus at 1st, 2nd and 3rd years are used as instruments in (VI)&(VIII). Mother's height and father's height were also included in all first stage equations to control for genetic variations in height. Site dummies were included in all the equations to control for community fixed effects.

Table A6. Average Marginal Effects of Child's height-for-age z-scores on the Choice probabilities of Various Child Activities (Older Cohort)

| Model | p(stud=1\|x) | p(stud=1, work=0\|x) | p(stud=1, work=1\|x) | p(stud=0, work=1\|x) | p(stud=0, work=0\|x) | p(work=1\|x) |
|---|---|---|---|---|---|---|
| Biprobit | - | 0.001 | 0.037*** | -0.032*** | -0.006** | - |
| | | (0.005) | (0.008) | (0.009) | (0.003) | |
| Biprobit two-stage | - | 0.001 | 0.062 | -0.052 | -0.011 | - |
| | | (0.036) | (0.049) | (0.065) | (0.017) | |
| Probit | 0.036*** | - | - | - | - | 0.008 |
| | (0.007) | | | | | (0.007) |
| Probit, two-stage | 0.079* | - | - | - | - | 0.011 |
| | (0.047) | | | | | (0.045) |
| Panel probit | 0.034*** | - | - | - | - | 0.011*** |
| | (0.007) | | | | | (0.004) |
| Panel prob. two- stage | 0.055 | - | - | - | - | 0.018 |
| | (0.049) | | | | | (0.027) |

*** p<0.01, ** p<0.05, *p<0.1

Notes: Tables A4 and A5 in this appendix respectively present coefficient estimates for bivariate probit and Probit results from which these partial effects were obtained. The partial effects reported in this table are the averages of partial effects calculated at each value of the child's height-for-age z- scores and the standard errors were calculated by the delta method. All models included controls for community fixed effects, child age and sex, land and livestock owned, household size and number of siblings, education of father and mother, distance to primary school, age of mother and father, and sex of household head.

Table A7. Average Marginal Effects of Child's height-for-age z-scores on the Choice probabilities of various Child Activities (Younger Cohort)

| Model | p(stud=1\|x) | p(stud=1, work=0\|x) | p(stud=1, work=1\|x) | p(stud=0, work=1\|x) | p(stud=0, work=0\|x) | p(work=1\|x) |
|---|---|---|---|---|---|---|
| Biprobit | - | 0.005 | 0.021*** | -0.017*** | -0.009*** | - |
| | | (0.003) | (0.004) | (0.005) | (0.002) | |
| Biprobit two-stage | - | -0.004 | 0.080*** | -0.034 | -0.041*** | - |
| | | (0.019) | (0.022) | (0.027) | (0.014) | |
| Probit | 0.026*** | - | - | - | - | 0.007 |
| | (0.005) | | | | | (0.015) |
| Probit, two-stage | 0.073** | - | - | - | - | 0.043 |
| | (0.029) | | | | | (0.029) |
| Panel probit | 0.029*** | - | - | - | - | 0.002 |
| | (0.005) | | | | | (0.004) |
| Panel probit-two stage | 0.082** | - | - | - | - | 0.040 |
| | (0.032) | | | | | (0.027) |

***p<0.01, ** p<0.05, * p<0.1

Notes: Tables A4 and A5 in this appendix respectively present coefficient estimates for bivariate probit and Probit results from which these partial effects were obtained. The partial effects reported in this table are the averages of partial effects calculated at each value of the child's height-for-age z- scores and the standard errors were calculated by the delta method. All models included controls for community fixed effects, child age and sex, land and livestock owned, household size and number of siblings, education of father and mother, distance to primary school, age of mother and father, and sex of household head.

Table A8. Semi-Nonparametric Bivariate Estimates for Child Schooling and Work

| | Older Cohort | | Younger Cohort | |
|---|---|---|---|---|
| | I | II | III | IV |
| Variables | SNP | 2-Stage SNP | SNP | 2-Stage SNP |
| **Stud** | | | | |
| Child's Height-for-age z-scores | 0.169*** | 0.334 | 0.097*** | 0.304*** |
| | (0.042) | (0.222) | (0.022) | (0.100) |
| Sex | 0.468*** | 0.499*** | 0.353*** | 0.410*** |
| | (0.105) | (0.113) | (0.089) | (0.103) |
| Age | 0.046 | 0.066 | 0.223*** | 0.230*** |
| | (0.029) | (0.043) | (0.028) | (0.027) |
| Total Agricultural Land Area Owned | -0.031 | -0.035 | 0.010 | 0.009 |
| | (0.038) | (0.038) | (0.034) | (0.034) |

| | | | | |
|---|---|---|---|---|
| Total Tropical Livestock Units Owned | 0.012 | 0.013 | 0.027*** | 0.028*** |
| | (0.012) | (0.012) | (0.010) | (0.010) |
| Father's Education-at Least Primary | 1.129*** | 1.076*** | 0.484*** | 0.428*** |
| | (0.229) | (0.237) | (0.131) | (0.133) |
| Mother's Education-at Least Primary | -0.045 | -0.016 | 0.494** | 0.562*** |
| | (0.517) | (0.514) | (0.198) | (0.193) |
| Distance to the Nearest Primary School | 0.031 | 0.036 | -0.071*** | -0.069*** |
| | (0.033) | (0.035) | (0.022) | (0.022) |
| Household Size | 0.034 | 0.038 | -0.030 | -0.035 |
| | (0.031) | (0.031) | (0.023) | (0.023) |
| Number of Siblings | 0.001 | -0.005 | 0.053* | 0.061** |
| | (0.035) | (0.036) | (0.029) | (0.029) |
| Age of Father | -0.006 | -0.006 | -0.009 | -0.009 |
| | (0.008) | (0.008) | (0.007) | (0.007) |
| Age of Mother | 0.005 | 0.002 | 0.005 | 0.004 |
| | (0.009) | (0.009) | (0.008) | (0.008) |
| Sex of Household Head | -0.032 | -0.028 | 0.125 | 0.135 |
| | (0.168) | (0.167) | (0.129) | (0.129) |
| year04 | | | 0.164 | 0.139 |
| | | | (0.189) | (0.197) |
| Child's Height-for-age z-scores | | | | |
| Resid. from Height-for-age eqn. | | -0.168 | | -0.212** |
| | | (0.227) | | (0.099) |
| **work** | | | | |
| Child's Height-for-age z-scores | 0.032 | -0.369 | 0.030 | 0.149 |
| | (0.046) | (0.269) | (0.022) | (0.093) |
| Sex | -0.321** | -0.390*** | -0.072 | -0.050 |
| | (0.135) | (0.144) | (0.087) | (0.090) |
| Age | 0.131*** | 0.061 | 0.250*** | 0.248*** |
| | (0.033) | (0.051) | (0.029) | (0.033) |
| Total Agricultural Land Area Owned | 0.008 | 0.021 | 0.105** | 0.105** |
| | (0.050) | (0.050) | (0.048) | (0.049) |
| Total Tropical Livestock Units Owned | 0.007 | 0.006 | -0.000 | 0.001 |
| | (0.022) | (0.022) | (0.013) | (0.013) |
| Father's Education-at Least Primary | -0.204 | -0.104 | -0.193 | -0.237* |
| | (0.287) | (0.312) | (0.125) | (0.126) |
| Mother's Education-at Least Primary | 0.489 | 0.437 | 0.181 | 0.210 |
| | (0.511) | (0.518) | (0.204) | (0.208) |
| Distance to the Nearest Primary School | 0.065** | 0.042 | 0.071** | 0.068** |
| | (0.031) | (0.034) | (0.031) | (0.031) |
| Household Size | -0.021 | -0.036 | 0.016 | 0.012 |
| | (0.036) | (0.037) | (0.023) | (0.023) |
| Number of Siblings | -0.009 | 0.008 | -0.041 | -0.037 |
| | (0.037) | (0.040) | (0.030) | (0.030) |
| Age of Father | 0.001 | 0.002 | 0.011** | 0.010* |
| | (0.010) | (0.010) | (0.006) | (0.006) |
| Age of Mother | 0.009 | 0.014 | 0.004 | 0.002 |
| | (0.012) | (0.012) | (0.008) | (0.008) |
| Sex of Household Head | 0.417** | 0.387** | 0.106 | 0.097 |

| | | | | |
|---|---|---|---|---|
| | (0.189) | (0.190) | (0.135) | (0.138) |
| year04 | | | -0.091 | -0.086 |
| | | | (0.210) | (0.221) |
| g_1_1 | -0.685*** | -0.684*** | -0.066 | -0.057 |
| | (0.042) | (0.042) | (0.074) | (0.088) |
| g_2_1 | 0.058** | 0.053** | 0.270*** | 0.268*** |
| | (0.023) | (0.023) | (0.042) | (0.042) |
| g_1_2 | | | -0.225*** | -0.225*** |
| | | | (0.023) | (0.024) |
| g_2_2 | | | -0.070*** | -0.069*** |
| | | | (0.017) | (0.014) |
| Standard Deviation (s) | 1.281 | 1.281 | 1.301 | 1.300 |
| Standard Deviation (w) | 1.279 | 1.279 | 1.342 | 1.340 |
| Variance (s) | 1.642 | 1.640 | 1.692 | 1.690 |
| Variance(w) | 1.636 | 1.635 | 1.801 | 1.796 |
| Skewness(s) | -0.072 | -0.066 | -0.397 | -0.395 |
| Skewness(w) | -0.005 | -0.005 | 0.331 | 0.329 |
| Kurtosis(s) | 2.550 | 2.551 | 3.127 | 3.124 |
| Kurtosis(w) | 2.527 | 2.531 | 3.055 | 3.053 |
| rho | -0.557 | -0.559 | -0.484 | -0.482 |
| Observations | 1116 | 1116 | 2241 | 2241 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The bivariate binary-choice models were estimated through the semi-nonparametric estimators of Gallant and Nychka (1987). The unknown density of the latent regression errors is approximated by a Hermite polynomial expansion of order 2 for and 1 for the schooling and work equations for the older cohort and order 2 in both equations for the younger cohort. Convergence was hard to obtain with higher order polynomials because of the non-concavity of the log pseudolikelihood function.

## Appendix B. Robustness to Missing Rainfall Data

Table B1. Missing Monthly Rainfall Records for the 8 Critical Years in the Analysis of the Younger Cohort

| | Year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Site | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
| Adado | 3 | 0 | 0 | 5 | 0 | 3 | 0 | 0 |
| Adele Keke | 0 | 0 | 0 | 0 | 1 | 12 | 12 | 12 |
| Aze Deboa | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| Debre berhan | 2 | 0 | 0 | 1 | 0 | 3 | 1 | 1 |
| Dinki | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Doma'a | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| Gara Godo | 4 | 1 | 1 | 1 | 2 | 2 | 0 | 0 |
| Geblen | 12 | 12 | 12 | 12 | 5 | 0 | 0 | 0 |
| Haresaw | 8 | 12 | 12 | 12 | 4 | 0 | 0 | 3 |
| Imdibir | 0 | 0 | 0 | 0 | 1 | 0 | 12 | 4 |
| Koro degaga | 0 | 0 | 0 | 4 | 4 | 2 | 0 | 0 |
| Shumsha | 0 | 5 | 12 | 12 | 6 | 1 | 0 | 1 |
| Sirbana Gudeti | 0 | 0 | 1 | 4 | 0 | 0 | 1 | 0 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Tirufe Kecheme | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 |
| Yetmen | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 |

Table B2. Availability of Rainfall Data During the Main Rainy Season

| | Year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Site | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
| Adado | A | A | A | A | A | A | A | A |
| Adele Keke | A | A | A | A | A | NA | NA | NA |
| Aze Deboa | A | A | A | A | A | A | A | A |
| Debre berhan | A | A | A | A | A | A | A | A |
| Dinki | A | A | A | A | A | A | A | A |
| Doma'a | A | A | A | A | A | A | A | A |
| Gara Godo | A | A | A | A | A | A | A | A |
| Geblen | NA | NA | NA | NA | A | A | A | A |
| Haresaw | NA | NA | NA | NA | A | A | A | A |
| Imdibir | A | A | A | A | A | A | NA | A |
| Koro degaga | A | A | A | A | A | A | A | A |
| Shumsha | A | A | NA | NA | A | A | A | A |
| Sirbana Gudeti | A | A | A | A | A | A | A | A |
| Tirufe Kecheme | A | A | A | A | A | A | A | A |
| Yetmen | A | A | A | A | A | A | A | A |

Notes: A stands for "data available" and NA stands for "data not available".

Table B3. Two-Stage Bivariate Probit Results-Successively Adjusting the Estimation Sample for the Major Missing Rainfall Records

| VARIABLES | (I) | (II) | (III) | (IV) |
|---|---|---|---|---|
| **Student** | | | | |
| Child's Height-for-age z-scores | 0.251*** | 0.259*** | 0.233** | 0.226** |
| | (0.095) | (0.095) | (0.101) | (0.105) |
| Sex | 0.324*** | 0.326*** | 0.315*** | 0.314*** |
| | (0.070) | (0.070) | (0.072) | (0.072) |
| Age | 0.199*** | 0.199*** | 0.200*** | 0.210*** |
| | (0.018) | (0.019) | (0.020) | (0.021) |
| Total Agricultural Land Area Owned | -0.002 | -0.007 | -0.006 | -0.003 |
| | (0.024) | (0.023) | (0.024) | (0.023) |
| Total Tropical Livestock Units Owned | 0.024*** | 0.024*** | 0.023*** | 0.022*** |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Father's Education-at Least Primary | 0.349*** | 0.362*** | 0.377*** | 0.370*** |
| | (0.107) | (0.107) | (0.109) | (0.114) |
| Mother's Education-at Least Primary | 0.472*** | 0.489*** | 0.494*** | 0.502*** |
| | (0.143) | (0.144) | (0.148) | (0.153) |
| Distance to the Nearest Primary School | -0.027* | -0.031** | -0.027* | -0.026 |
| | (0.016) | (0.016) | (0.016) | (0.016) |

| | | | | |
|---|---|---|---|---|
| Household Size | -0.030* | -0.027* | -0.030* | -0.028 |
| | (0.016) | (0.017) | (0.017) | (0.017) |
| Number of Siblings | 0.052** | 0.054** | 0.056** | 0.061*** |
| | (0.021) | (0.022) | (0.022) | (0.023) |
| Age of Father | -0.006 | -0.007 | -0.007 | -0.005 |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Age of Mother | 0.001 | 0.001 | 0.003 | 0.002 |
| | (0.006) | (0.006) | (0.006) | (0.007) |
| Sex of Household Head | 0.113 | 0.079 | 0.077 | 0.079 |
| | (0.094) | (0.096) | (0.099) | (0.105) |
| Resid. from Height-for-age eqn. | -0.169* | -0.175* | -0.150 | -0.141 |
| | (0.095) | (0.095) | (0.100) | (0.105) |
| Year=2004 | 0.043 | 0.065 | 0.069 | 0.045 |
| | (0.105) | (0.111) | (0.112) | (0.115) |
| Constant | -1.892*** | -1.965*** | -2.059*** | -2.229*** |
| | (0.390) | (0.389) | (0.407) | (0.416) |
| **Work** | | | | |
| Child's Height-for-age z-scores | 0.162 | 0.176* | 0.189* | 0.174 |
| | (0.103) | (0.102) | (0.106) | (0.115) |
| Sex | -0.035 | -0.068 | -0.098 | -0.119* |
| | (0.065) | (0.066) | (0.068) | (0.069) |
| Age | 0.141*** | 0.148*** | 0.140*** | 0.140*** |
| | (0.018) | (0.019) | (0.020) | (0.021) |
| Total Agricultural Land Area Owned | 0.081** | 0.080** | 0.076** | 0.073** |
| | (0.037) | (0.037) | (0.037) | (0.037) |
| Total Tropical Livestock Units Owned | 0.002 | 0.002 | 0.002 | 0.002 |
| | (0.011) | (0.011) | (0.011) | (0.012) |
| Father's Education-at Least Primary | -0.200** | -0.190* | -0.177* | -0.193* |
| | (0.095) | (0.097) | (0.099) | (0.101) |
| Mother's Education-at Least Primary | 0.140 | 0.144 | 0.140 | 0.128 |
| | (0.148) | (0.150) | (0.153) | (0.158) |
| Distance to the Nearest Primary School | 0.041** | 0.041** | 0.045** | 0.045** |
| | (0.021) | (0.021) | (0.021) | (0.021) |
| Household Size | 0.010 | 0.006 | 0.006 | 0.009 |
| | (0.017) | (0.018) | (0.018) | (0.019) |
| Number of Siblings | -0.030 | -0.031 | -0.030 | -0.036 |
| | (0.023) | (0.024) | (0.024) | (0.025) |
| Age of Father | 0.004 | 0.004 | 0.004 | 0.004 |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Age of Mother | 0.002 | 0.003 | 0.003 | 0.003 |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Sex of Household Head | 0.025 | 0.087 | 0.077 | 0.103 |
| | (0.099) | (0.103) | (0.107) | (0.112) |
| Resid. from Height-for-age eqn. | -0.152 | -0.169 | -0.188* | -0.170 |
| | (0.105) | (0.104) | (0.108) | (0.117) |
| Year=2004 | 0.080 | 0.015 | 0.080 | 0.097 |
| | (0.109) | (0.114) | (0.118) | (0.120) |
| Constant | -0.467 | -0.355 | -0.349 | -0.388 |
| | (0.389) | (0.400) | (0.408) | (0.422) |
| Athrho | -0.521*** | -0.518*** | -0.510*** | -0.522*** |

| | | | | |
|---|---|---|---|---|
| | (0.053) | (0.054) | (0.055) | (0.057) |
| Observations | 2241 | 2145 | 2053 | 1958 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Site dummies were included in all equations to control for community fixed effects. Equation (I) was estimated using the entire sample. Equation (II) includes in the estimation sample only those who had at least 6 months of non-missing monthly rainfall records including the main rainy (agricultural) season during at least 1 of their critical years of development. The 5 and 6 year olds from Geblen and Haresaw and 1 year olds from Adele Keke did not fulfill these criteria and were excluded from the estimation sample for (II). Equation (III) includes in the estimation sample only those who had at least 6 months of non-missing monthly rainfall records including the main rainy (agricultural) season during at least 2 of their critical years of development. The 4, 5 and 6 year olds from Geblen and Haresaw, 1 and 2 year olds from Adele Keke and 4 year olds from Shumsha did not fulfill these criteria and were excluded from the estimation sample for (III). Equation (IV) includes in the estimation sample only those who had at least 6 months of non-missing monthly rainfall records including the main rainy (agricultural) season for all of the 3 critical years of development. The 3, 4, 5 and 6 year olds from Geblen and Haresaw, 1, 2 and 3 year olds from Adele Keke, 3 and 4 year olds from Shumsha, and 1 and 2 year olds from Imdibir did not fulfill these criteria and were excluded from the estimation sample for (IV).

Table B4. First-Stage Results for the Younger Cohort-Successively Adjusting the Estimation Sample for the Major Missing Rainfall Records

| VARIABLES | (I) | (II) | (III) | (IV) |
|---|---|---|---|---|
| Substantial rainfall deficit at 1st year | 0.047 | 0.021 | 0.052 | 0.059 |
| | (0.223) | (0.226) | (0.233) | (0.244) |
| Substantial rainfall deficit at 2nd year | -0.401** | -0.396** | -0.379** | -0.371** |
| | (0.179) | (0.179) | (0.181) | (0.178) |
| Substantial rainfall deficit at 3rd year | -0.243 | -0.240 | -0.212 | -0.246 |
| | (0.178) | (0.178) | (0.180) | (0.181) |
| Substantial rainfall surplus at 1st year | -0.030 | -0.088 | -0.067 | -0.046 |
| | (0.178) | (0.196) | (0.197) | (0.198) |
| Substantial rainfall surplus at 2nd year | -0.227 | -0.247 | -0.224 | -0.179 |
| | (0.180) | (0.181) | (0.182) | (0.186) |
| Substantial rainfall surplus at 3rd year | -0.094 | -0.090 | -0.041 | -0.147 |
| | (0.251) | (0.251) | (0.261) | (0.273) |
| Height of Mother | 0.028*** | 0.037*** | 0.037*** | 0.035*** |
| | (0.010) | (0.011) | (0.011) | (0.011) |
| Height of Father | 0.027*** | 0.026*** | 0.024*** | 0.026*** |
| | (0.008) | (0.008) | (0.008) | (0.009) |
| Sex | -0.223*** | -0.207*** | -0.199 | -0.176 |
| | (0.119) | (0.121) | (0.124) | (0.128) |
| Age | -0.020 | -0.035 | -0.050 | -0.054 |
| | (0.032) | (0.034) | (0.034) | (0.035) |
| Household Size | 0.016 | 0.025 | 0.021 | 0.015 |
| | (0.025) | (0.024) | (0.024) | (0.025) |
| Number of Siblings | -0.034 | -0.038 | -0.032 | -0.029 |
| | (0.035) | (0.035) | (0.037) | (0.036) |
| Sex of Household Head | -0.102 | -0.125 | -0.173 | -0.207 |
| | (0.157) | (0.164) | (0.170) | (0.178) |
| Father's Education-at Least Primary | 0.200 | 0.180 | 0.225 | 0.199 |

| | (I) | (II) | (III) | (IV) |
|---|---|---|---|---|
| | (0.188) | (0.191) | (0.193) | (0.194) |
| Mother's Education-at Least Primary | -0.343 | -0.326 | -0.399 | -0.404 |
| | (0.260) | (0.263) | (0.253) | (0.259) |
| Age of Father | 0.004 | 0.002 | 0.002 | 0.001 |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Age of Mother | 0.009 | 0.012 | 0.016 | 0.018 |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Total Agricultural Land Area Owned | 0.003 | -0.000 | 0.002 | -0.005 |
| | (0.032) | (0.032) | (0.032) | (0.032) |
| Total Tropical Livestock Units Owned | -0.011 | -0.012 | -0.011 | -0.009 |
| | (0.010) | (0.010) | (0.011) | (0.010) |
| Year=2004 | 0.108 | 0.189 | 0.236 | 0.231 |
| | (0.167) | (0.175) | (0.177) | (0.180) |
| Constant | -11.453*** | -12.668*** | -12.541*** | -12.362*** |
| | (1.901) | (1.943) | (2.014) | (2.087) |
| Observations | 2241 | 2145 | 2053 | 1958 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Site dummies were included in all equations to control for community fixed effects. Equations (I), (II), (III) and (IV) are first-stage results for equations (I), (II), (III) and (IV) in table B3, respectively.

Table B5. Marginal effects (at mean value) of Child's Height-for-age z-scores on the Choice Probabilities of Various Child Activities from the Two-Stage Bivariate Probit Results in Table B2

| Model | p(stud=1\|x) | p(stud=1, work=0\|x) | p(stud=1, work=1\|x) | p(stud=0, work=1\|x) | p(stud=0, work=0\|x) | p(work=1\|x) |
|---|---|---|---|---|---|---|
| (I) | 0.100*** | -0.013 | 0.113*** | -0.064* | -0.036*** | 0.048 |
| | (0.038) | (0.023) | (0.032) | (0.035) | (0.012) | (0.031) |
| (II) | 0.103*** | -0.014 | 0.117*** | -0.065* | -0.038*** | 0.052* |
| | (0.038) | (0.023) | (0.032) | (0.035) | (0.011) | (0.030) |
| (III) | 0.093*** | -0.018 | 0.111*** | -0.055 | -0.038*** | 0.056* |
| | (0.040) | (0.023) | (0.034) | (0.037) | (0.013) | (0.031) |
| (IV) | 0.090** | -0.016 | 0.106*** | -0.055 | -0.036*** | 0.051 |
| | (0.042) | (0.025) | (0.036) | (0.038) | (0.013) | (0.034) |

*** p<0.01, ** p<0.05, * p<0.1

Notes: The partial effects reported in this table were calculated at the mean value of the child's height-for-age z- scores and other regressors and the standard errors were calculated by the delta method. Rows (I), (II), (III) and (IV) come from the results reported under equations (I), (II), (III) and (IV) in table B3, respectively.