140
Working Paper

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An International Study of Childhood Poverty

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Results from Young Lives in Ethiopia

Tassew Woldehanna and Aregawi Gebremedhin

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Abstract

The objective of this study is to explore the effect of child work on school achievement as measured by the Peabody Picture Vocabulary Test (PPVT). Identifying the causal effects of child work on education is made difficult because the choice of work and/or school is made simultaneously and may be determined by the same potentially unobserved factors. Therefore, both ordinary least square and instrumental variable estimation methods were used to identify the effect of child work on school achievement. We used dummy variables for drought, crop failure and pests and diseases, for increases in the prices of food, and for urban locality as instruments which are highly, though not directly, correlated with achievement in education. The results obtained showed that child work had a negative effect on child achievement in education as measured by the raw PPVT score. Therefore, it is important to design mechanisms that enable households to withstand income shocks without resorting to child work. The Government of Ethiopia should consider implementing a programme that provides financial incentives to households to send their children to school regularly, thus potentially increasing the children's future earning capacity. A conditional cash transfer programme could be a way of helping children achieve better in school and of minimising child work.

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About Young Lives

Young Lives is an international study of childhood poverty, following the lives of 12,000 children in 4 countries (Ethiopia, India, Peru and Vietnam) over 15 years. **www.younglives.org.uk**

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1. Introduction

Parents have discretion over the allocation of their children's time to different activities. Although schooling increases future earnings, as argued by Glewwe (2002), poor parents fail to send their children to school for two reasons. The first is that they do not have the financial ability to cover the direct costs of sending their children to school, while the second is that the opportunity cost of the children's time is very high. As a general rule, the expected future earnings of children must outweigh the current costs of sending children to school for parents to enrol their children in school, assuming there are perfect capital markets to smooth the consumption of households. (Glewwe and Jacoby 1994)

In the absence of perfect capital markets, which is true virtually everywhere and especially for developing countries, it is difficult for parents to smooth their current consumption by borrowing to cover the opportunity cost of their children's time in school with the expectation of higher future earnings for the children (Brown and Park 2002).

Given the importance of education for children's future earnings, it is vital to explore whether child work has an effect on education and, if so, to measure the extent of its effect and to identify points of policy intervention.

However, when one tries to investigate how child work affects children's education, one can observe that it is difficult to establish a causal relationship as there are other factors that simultaneously affect child work and education. The opportunity cost of the child's time, i.e., the price for the time of the children that parents assign, determines both education and child work. Therefore, it is important to find a variable that is correlated with child work but not with education, so that the causal effect of child work on educational attainment is established (Ravallion and Wodon 2000).

Two studies have been conducted by Young Lives that have explored the relationship between child labour and education in Ethiopia. The first study is Woldehanna et al. (2005), which investigated parents' decisions on schooling using a multinomial logit model. In this study the determinants of parents' choices among education, child work and a combination of both were identified. The second study is Woldehanna and Hagos (2012), which explored the effect of shocks on children dropping out of primary school using an accelerated failure-time hazard model. Among the variables that were controlled for was child work. However, neither of these studies explored the relationship between child work and education after dealing with the simultaneity between the two variables, which is necessary to ensure a causal relationship.

In this study, the term 'child work' will refer to any form of participation by children in paid or unpaid work activities. In the Young Lives research, at each survey round, children are asked how they spent their time on a typical day in the previous week, and it is from these data that the current study has taken the number of hours children work.

The Ethiopian Government has been directing its resources to achieving the second Millennium Development Goal, i.e., universal primary education. Moreover, it has also started working on retaining children in school and improving the quality of the education they receive. However, the existence of poor households, especially in the rural areas, which are more likely to allocate more time to child work than to education as the credit constraints are more binding for them, is one of the primary concerns of the policymakers. The accumulation of human capital has an irreplaceable role in the country's development endeavour.

Therefore, it is important to identify the causal effects of child work on education and the extent of those effects.

This study adds value to the previous work done by Young Lives by dealing with the problem of endogeneity to establish a causal relationship between child work and education. This will improve the reliability of the evidence to be used for policymaking. Although several studies have been conducted in other developing countries, no study has been conducted in Ethiopia to explore the relationship of child work and education while dealing with the endogenous nature of child work. In addition to dealing with simultaneity, the study uses test scores as outcomes rather than more commonly used measures of education such as enrolment rates and primary school completion rates. This helps to assess the effect of child work on the cognitive development of children as the data contain scores for all children in the sample and not just those who are enrolled in school. And this makes the study unique as most of the studies on child work and schooling in Ethiopia focus on the effect of children's work on school completion and drop-out rates, which are basically crude measures of education.

Therefore, the aim of this study is to investigate the causal effect of child work on education. The specific objectives are to:

1. explore the causal effect of child work on educational attainment
2. investigate the extent of its effect and identify points for policy intervention.

To this effect, the study uses the Round 2 and Round 3 data collected in Ethiopia in 2006 and 2009 respectively by Young Lives, which has compiled a unique panel dataset on children's welfare and their families' livelihoods (see Section 4 for more details). The data used are from the Older Cohort because most of the children in the Younger Cohort were not enrolled in school in Round 2. Moreover, they were enrolled in lower grades in Round 3. Regarding the methods of analysis, the study uses both ordinary least square (OLS) and instrumental variable (IV) estimation methods to capture the relationship between child work and education. In particular, the IV method is used to explore the causal effect child work has on education. A sensitivity analysis will also be conducted to check for the robustness of the results to different methods.

The remaining parts of the paper are organised as follows. In Section 2 a review of literature is presented, while Section 3 presents the data and methods. Section 4 discusses the descriptive statistics and Section 5 presents the results and discussion. Section 6 provides concluding remarks.

2. Review of literature

2.1. The effect of child work on school attainment

Several studies have investigated the relationship between child work or child labour and different indicators of educational attainment. According to the International Labour Organization (ILO) Conventions 138 and 182, child labourers are all persons under 18 years engaged in labour market or household activities that may interfere with their development. The ILO criteria for identifying any given work as child labour include: a child under 12 who participated in an economic activity for at least one hour per week, a child aged 12 to 14 who participated for at least 14 hours per week (two hours per day), and a child aged 15 to 17 who participated for at least 43 hours per week.[1] Heady (2000) investigated the effect of child labour on the learning achievement of children in Ghana and found a negative effect of child labour on test scores. Similarly, Rosati and Rossi (2001) obtained an inverse relationship between child work and the test scores of children in Pakistan and Nicaragua. Gunnarson et al. (2006) also found that child labour had a negative effect on the educational attainment in 11 countries in Latin America.

On the other hand, researchers such as Ravallion and Wodon (2000), who analysed a sample in Bangladesh, found that child labour and schooling were mutually exclusive activities and that they might even complement each other. Similarly, Patrinos and Psacharopoulos (1997) found that the child labour and school were mutually exclusive in Peru.

Studies such as Beegle et al. (2003), Watson (2008), Bezerra et al. (2009), Beegle et al. (2009) and Mavrokonstantis (2011) have explored the causal effect of child labour on schooling. Unlike other studies that have focused on identifying the trade-off between child labour and schooling, these studies tried to see whether there was a causal relationship between the two variables. All of these studies used IV methods to deal with the endogenous nature of child labour. As will be discussed below, the results of these studies are mixed.

After instrumenting child labour with crop shocks experienced at the community level and rice prices Beegle et al. (2003) found that children between the ages of 7 and 13 years engaging in labour were less likely to be in school four years later. Children were also found to lag behind in terms of their grade in addition to the lower educational attainment caused by their engagement in labour activities.

Specifically, Beegle et al. (2003) examined the relationship between household income shocks and child labour in Tanzania, viewing crop shocks as transitory shocks to household income. They found that crop shocks significantly led to increases in child labour and decreases in educational enrolment, but households with asset holdings were able to fully offset the shocks without resorting to child labour. So the decrease in educational enrolment due to the crop shocks could possibly have resulted from the fact that children were sent to work instead of school to respond to the shocks.

1 For details, see http://www.ilo.org/ipec/facts/ILOconventionsonchildlabour/langen/index.htm (accessed on 19 Jan 2015). We use different definitions in this study when testing the effects of more intensive child work on schooling. For details, please see Section 3.2. The authors cited in this literature review may have defined these terms in their own way.

Beegle et al. (2009) also investigated the impact of child labour on health, education and waged work over a five-year period using an IV method. They found that child labour had a significant effect on school participation and educational attainment but no significant impact on subsequent health.

In addition, Bezerra et al. (2009) used the average wage for unskilled male labour as an instrument for child labour. The results of the study showed that child labour reduced children's school achievement. Moreover, children who did not work were found to have a better school performance than those who did. Regarding the intensity of the effect of child work on achievement, child work for up to two hours per day was not found to have a statistically significant effect. However, child work beyond two hours per day was found to have a negative effect on schooling.

On the other hand, Watson (2008) used different shock variables that were experienced at both the household and community levels as an instrument for child labour. Over-identifying restrictions were also tested in this study. The results of the study showed that child labour did not have an effect on schooling.

Mavrokonstantis (2011) studied the effect of child labour on the educational attainment of children in Vietnam using Young Lives longitudinal data and employing the IV method. He used two instruments, community-level rice prices and log per capita asset value, to identify the causal effects of child labour on education, and found that the effect of child labour on educational attainment was insignificant in rural areas but that a causal effect of child labour and education was evident in urban areas.

2.2. Determinants of child work and educational attainment

Several studies have identified factors that have determined child labour and schooling. Among these factors, the major ones are household composition, gender of child, location of household (rural/urban), parental education, gender of the head of the household, access to credit, school and community infrastructure, income, ownership of land and livestock, and asset ownership. The number of household members influences the incidence and intensity of child labour by affecting household members' productivity or reduction in wage level (see inter alia Cockburn and Dostie 2007 and Rosati and Rossi 2001). The gender of children also affects the allocation of their time to different activities (see, for example, Cockburn and Dostie 2007; Gunnarsson et al. 2006; Ersado 2005; Ray 2000; Woldehanna and Hagos 2012; Islam and Choe 2009). Besides, several empirical studies confirm that the location of households (Gunnarsson et al. 2006; Ray 2000; Rosati and Rossi 2001), parental education (Gunnarsson et al. 2006; Ersado. 2005; Rosati and Rossi 2001; Ray 2000), the gender of the household head (Cockburn and Dostie 2007; Galiano 2009), access to credit (Ersado 2005; Dehejaia and Gatti 2002; Islam and Choe 2009), the income of households (Galiano 2009), and land or asset ownership of households (Cockburn and Dostie 2007; Beegle et al. 2006) were among the socio-economic and demographic variables identified as having an impact on child labour.

2.3 The methodological challenges

The literature on the relationship between child work/labour and the educational attainment of children raises a number of methodological issues. Perhaps the most obvious is how to measure educational attainment. Another important point is the endogeneity in the hours worked per day. For instance, child work can be seen as a pre-determined factor that affects a child's ability to go to school, or decisions on schooling and work could be taken simultaneously.

When measuring educational attainment, most research papers which focus on the effect of child labour on the educational attainment of children rely on the effect of this labour on school enrolment, attendance or drop out. For instance, Ersado (2005) investigated the drivers of child labour making use of data on child labour participation and education decisions, and in the context of this study educational attainment was defined as whether the child attended school or not. Similarly, Galiano (2009) and Ray (2000) explored the effect of child labour on school attendance. Islam and Choe (2009) measured educational attainment using school enrolment in their study. Moreover, Woldehanna and Hagos (2012) used the likelihood of children completing primary education or dropping out of primary school as a measure of educational attainment. Nevertheless, school enrolment, attendance and drop out are not perfect measures of educational attainment because children may still allot some time to schooling but their outcome could be lower and hence the effect of child labour could not be seen. Alternatively, a few studies (e.g. Gunnarsson et al. 2006; Mavrokonstantis 2011; Watson 2008; Heady 2000) have used test scores as a measure of educational attainment and this could best assess the performance of children in school.

Regarding the issue of endogeneity, some studies have recognised the simultaneous determination of schooling and child labour. Some of these have tried to capture the joint responses of schooling and child labour to changes in other variables. These studies adopted a bivariate probit model to examine the interdependence between decisions on child labour and schooling only considering the trade-off in the time allocated to the two instead of investigating the effect of one on the other. One of such studies is Ersado (2005), which investigated the drivers of child labour, making use of data on child labour participation and education decisions. Another study that used a bivariate probit model to identify the determinants of child labour and school attendance is Galiano (2009). Islam and Choe (2009) and Dillon (2008) also used multivariate models to examine the child labour responses to micro-credit and production and health shocks respectively. Although the bivariate model is a powerful way of looking at the responses of interrelated variables, by allowing the error terms of child labour and schooling regressions to be correlated, it lacks the ability to establish a causal relationship between such variables. The results of these studies can indicate the trade-offs between the two variables but not how one of them affects the other.

A few studies have used different identification strategies to deal with the endogenous nature of child labour, utilising the IV method. Gunnarson et al. (2006) exploited the benefits of a cross-country study by using cross-country variation in schooling ages and truancy laws as an instrument for child labour. This instrument was used to predict a categorical variable on the incidence of child labour, the predicted values of which were used to estimate the school achievement equations. Similarly, Beegle et al. (2003) used crop shocks experienced at the community level and rice prices as instruments for child labour, as crop shocks are negatively related to child labour. Similarly, Watson (2008) used household- and community-level shocks as instruments for child labour in her estimation strategy and conducted an over-identification test to check whether the instrumental variables adopted were relevant. On the other hand, Bezerra et al. (2009) used an instrument that reflected the condition of the local labour market, namely the average wage earned by male workers aged 20 to 30 who had not completed primary education.

3. Theoretical and empirical model

3.1. Theoretical model

We start with the education production function as discussed in Gunnarsson and Orazem (2003). Educational achievement is measured by test scores, $H_{ijt,}$ of the i^{th} child living with j^{th} household at time *t*. The current test scores are a function of child work status, household-, school- and community-level factors, and previous level of educational achievement or test scores. Hence the educational achievement is modelled as

$$H_{ijt} = H(C_{ijt,}S_{ijt,}H_{ijt-1,}X_{ijt}\ ,K_{jt}) \tag{1}$$

where *H* is test scores, *C* is child work status, $S_{ijt,}$ are other inputs for cognitive skills such as years of schooling or grade completed, X_{ijt} are child-specific exogenous variables, K_{jt} are household-specific exogenous variables, and the subscripts *i* and *j* represent the child and the household respectively, and the subscript *t* refers to time where *t* stands for Round 3 while *t-1* represents Round 2.

Given the standard assumptions about a household's utility function and budget constraints, the labour supply function of children's labour supply is given by the following

$$C_{ijt} = C(W_{ijt}, M_{jt},\ Y_{jt}, X_{ijt}\ , K_{jt}, Z_{jt}) \tag{2}$$

where *W* is the market wage that could be earned by the child, *M* is the index of wage that could be earned by other household members and *Y* is non-labour income earned by the household.

3.2. Empirical model

An explanatory variable is called an endogenous variable when it is correlated with the error term. The correlation occurs if (a) there are omitted variables that are correlated with both the explanatory variable and the dependent variable, (b) the explanatory variable is measured with errors (commonly called measurement error), or (c) the dependent variable and the explanatory variable are simultaneously determined. For all of these problems, we can apply IV estimations because instrumental variables are used to cut correlations between the error term and independent variables. To conduct IV estimations, we need to have instrumental variables that are uncorrelated with the error term but strongly correlated with the endogenous variable once the other independent variables are controlled for.

Since the allocation of time to school comes at the cost of time to child labour (they are simultaneously determined), child labour would be endogenous, which means that the assumption that the explanatory variable is not correlated with the unobservable variables would be violated (Ravallion and Wodon 2000; and Beegle et al. 2006). In our case, past accumulation of cognitive achievement up to Round 2 is partly controlled for by including the previous test scores (Round 2 test scores) as an explanatory variable. However, there are contemporaneous unobserved household and child factors that are correlated with labour supply and also determine the productivity of cognitive skill inputs. This leads to a biased estimate of the effect of child labour on schooling. As a result, it would be difficult to draw a causal relationship between the two variables.

To deal with this problem, it is necessary to find an instrumental variable that is correlated with child labour but not with the unobservable variables that also determine schooling (which is the dependent variable). Using the two-stage least square estimation method, one can first estimate child work on the exogenous explanatory variables and the instruments. Afterwards, the predicted values of child work are included in the second stage when running schooling outcome on the other explanatory variables.

In this study, both OLS and IV estimation methods are used to explore the effect of child labour on school achievement. Since we are using a dataset from a single country; we cannot make use of inter-country differences as an instrument for child labour, as in Gunnarsson et al. (2006). Neither can we make use of local-level labour market information as in Bezerra et al. (2009), since we do not have such variables in our dataset. However, locality, which is measured by an urban dummy, is used as a proxy for local wage rates. Therefore, we resort to the instruments used by Beegle et al. (2003) and Watson (2008), which are (a) households' experience of crop shocks; (b) the price of certain foodstuffs; and (c) locality, as used by Beegle et al. (2009) and Mavrokonstantis (2011).

In line with Beegle et al. (2003) and Watson (2008), this study uses the incidences of drought, crop failure and pests and disease shocks the household face as an instrument to child work/labour. This variable assumes a value of 1 if the household experiences drought, crop failure and pests or diseases that affected crop and 0 otherwise. According to Watson (2008) these events are unexpected and when they happen households might need extra labour so as to sustain life and survive them. She found that the exogenous shocks, which she used as an instruments in her study, were highly and significantly correlated with child labour and remarked these shock instruments were the 'successful instruments'. Accordingly, this instrument is expected to increase child labour but not to affect children's educational outcomes directly except through the channel of child labour.

The second instrument is a dummy for shocks associated with an increase in the price of foods that the household buys. This instrument is in line with studies by Beegle et al. (2009) and Mavrokonstantis (2011), in which they employed community-level rice prices as an instrument for child labour. In both studies the increase in rice prices was found to be associated with a decrease in child labour, implying that the profit effect dominated the income effect. In rural areas, where households are net suppliers, the increase in food prices may lead households to reduce child labour because their income increases (income effect) or may lead to an increase in the demand for child labour because of the need to expand production (profit effect). But according to Mavrokonstantis (2011) the relevance of the instrument is not affected by the dominance of either of them. In urban areas, however, there is only an income effect, as the households are net consumers not producers of food and the increase in the price of foods leads to an increase in child labour. Besides, Mavrokonstantis (2011) argues that there is no way that an increase in rice prices could have a direct impact on educational outcomes except through child labour. Hence, this study adopts the dummy for the increase in the prices of food as a second instrument for child work. More than 85 per cent of households in our sample reported that they had faced a food price increase and our study will explore whether this increase in food prices had a significant effect on child work.

The third instrument is wages, which affect the labour supply directly and educational achievement indirectly via the labour supply. As wages vary by locality, locality measured by urban dummy could be a perfect candidate for an instrument. Usually urban wage rates are higher than rural wages in the slack season where there are no intensive agricultural activities, while rural wages vary across seasons. During the peak agricultural seasons rural wages rise, but always less than urban wages. Therefore urban dummy is a suitable indicator of variations in wage rates. Bezerra et al. (2009) made use of local level labour market information; i.e. the average wage for unskilled male labour in the state was used as an instrument for child labour in estimating the effect of child labour on school achievement in Brazil. However, since local wage rates in our dataset are subject to missing values, we used locality as a proxy for local wages and hence as an instrument for child work. Locality is expected to affect the raw scores of children through the channel of child work because it influences parents' decisions about whether to send their children to work or school and serves as a proxy for the local wage rate.

The between-household differences that may lead to a bias in the estimates of child work are dealt with by controlling for exogenous variables such as household composition, educational level of parents and a household's ownership of assets or wealth index.

The resulting model used for the estimation is:

$$H_{ijt} = \beta_0 + \beta_1 C_{ijt} + \beta_2 S_{ijt} + \beta_3 H_{ijt-1} + \beta_4 X_{ijt} + \beta_5 K_{jt} + \mathcal{E}_{ijt} \quad (3)$$

Where H_{ijt} is children's educational achievement, as measured by the raw scores in the Peabody Picture Vocabulary Test (PPVT); C_{ijt} is the number of hours a child spends working per day; $S_{ijt,}$ are other inputs for cognitive skills such as grade completed, X_{ijt} and K_{jt} are child-specific and household-specific exogenous variables respectively, including the age of a child in months, a dummy variable for a male child, household composition variables, a dummy for male-headed households, parental education variables and the wealth of the household (measured by a wealth index); *i* is a subscript for child, *j* is a subscript for household, and the subscript *t* refers to Round 3 and *t*-1 for Round 2. We have not included an enrolment dummy, as the highest grade completed can perhaps account for how much schooling children have had up to that point.

The reduced form equation of child work is a function of all exogenous variables in (3) plus the instruments of child work. Hence the first-stage equation of the IV estimation is given by:

$$C_{ijt} = \alpha_0 + \alpha_1 H_{ijt-1} + \alpha_2 S_{ijt} + \alpha_3 X_{ijt} + \alpha_4 K_{jt} + \alpha_5 Z_{jt} + \alpha_6 G_{jt} + e_{ijt} \quad (4)$$

Where *C* is the number of hours a child spends working per day, *G* is a control for locality that controls for local wages proxied by urban dummy and *Z* is a vector of dummy variables for a household's experience of shocks in the last four years. The predicted values of C_{ijt} are then included in the achievement model to estimate achievement so that consistent estimates of child work are obtained. However, the study used the 'ivreg2' command which uses the correct standard errors and automatically reports all the robustness tests.

In addition to the comparison that will be made between OLS and IV estimates, the sign, magnitude and statistical significance of child work resulting from a change in the explanatory variables used is also explored.

Moreover, to understand the difference in the sign and magnitude of the effect of child labour, the child work variable was used in two different forms. In the first form, all of the children in the sample are taken into consideration. In the remaining group the data are classified based on the participation of children in child work for more than two hours per day. Following the ILO definition of child labour,[2] the two-hours-per-day threshold was used to understand the effects of child labour (more than two hours per day) and just child work (less than two hours per day) on schooling. We tried to estimate the effects of child labour using the dummy for

2 See footnote 1. Young Lives explicitly considers both paid and unpaid domestic and extra-household work, thereby avoiding the gender bias of the ILO definition, which assigns less weight to domestic work (14 hours per week of productive work versus 28 hours of household-based work).

child labour and the interaction of child labour dummy with child work. We also estimated using a probit regression of the child labour dummy on the explanatory variables and instruments. After finding the fitted value from the probit regression we then estimated the second stage least square regression with the fitted value as an additional instrument to child labour. This produced insignificant estimators and led to weak identification, in which case we cannot infer causality. However, only 15 per cent of children were found working for two hours or fewer per typical day and the majority of the children worked for more than two hours per day. Hence, as most of the children in the sample were engaged in child labour (as per the ILO definition), estimating 'child work' and 'child labour' separately does not generate new findings but replicates the findings for all work done by the children in the sample. Estimating child work is similar to estimating child labour and due to this we only estimate child work. Furthermore, all the regressions are estimated with standard errors clustered at the sentinel site level.

4. Data and descriptive statistics

4.1. Data

This study utilised the Older Cohort data from the survey undertaken by Young Lives in Ethiopia, in which the same children are followed over the course of the 15-year study. The children were 12 years old in Round 2 (2006) and 15 years old in Round 3 (2009). The Older Cohort data are used because most of the children in the Younger Cohort were not enrolled in school in Round 2. Moreover, they were enrolled in lower grades in Round 3.

The sample contains 970 children, who live in 20 sentinel sites located in five of the regions in the country, namely Addis Ababa, Oromia, Amhara, SNNPR and Tigray. These regions were selected because 96 per cent of the population of the country lives there. The main selection criterion adopted for the sentinel sites was that they had to be located in poor areas, the definition of which was based on the country's food insecurity designations. Seventy-five per cent of the sentinel sites in each region were selected from high food-deficit *woredas* (districts) while 25 per cent were selected from a lower food-deficit *woreda*. The children in the rural areas comprise 60 per cent of the sample while 40 per cent are from urban areas. Each region comprises 20 per cent of the total sample, except for Addis Ababa, which contains 15 per cent of the sample and SNNPR, from which 25 per cent of the sample was selected.

Data on population density were also taken into account when sentinel sites were selected. Moreover, consultations were held with regional policymakers and other stakeholders. Within each sentinel site, a simple random sample of 100 households was taken.

4.2. Description of the variables in estimation

The various determinants of schooling achievement were identified in Section 2 of this paper and the ways in which they affect it were also discussed there. In this sub-section, we will discuss the specific variables used for analysis and how they are measured.

i **Child work:** This variable was generated from the sum of hours spent, per typical day in the previous week of the Round 3 survey, caring for others, doing domestic tasks, doing household farm activities (tasks on the family farm and cattle herding) and undertaking paid activities. The Young Lives data contain two sources of responses for children's hours of engagement in work/labour: one from the child and one from the caregiver. The current study used the one from the child because there was no significant difference between the two; for instance the average hours of work reported by the child was 5.05 and those given by the caregiver was 4.95. The values of this variable range between 0 and 15.

ii School achievement: The achievement of children is captured by their raw PPVT scores in Round 3 instead of the highest grade they completed.

iii Age in months: To capture the effect of the age of the children in the sample on school achievement, their age in months was included.

iv Household composition: The household composition variables are based on age group and gender. They include the number of household members aged below 7 years, between 7 and 17 years, between 17 and 65 years and older than 65 years. The number of people in each age group was also disaggregated by gender. The inclusion of these variables was designed to help us see whether changes in the household composition caused child work to increase and/or brought about a deterioration in children's achievement at school.

v Gender of child: The study controls for gender by using a dummy variable for male children. This variable is expected to make clear the effect of gender on school achievement and whether there is gender inequality in school achievement.

vi Parental education: The highest education level achieved by both fathers and mothers was controlled for in the different regressions to capture the effect of parental education on children's achievements.

vii Gender of head of household: The variable used to capture the effect of the gender of the head of household is a dummy variable for female head of household.

viii Wealth index: This variable is included in the regressions as a proxy for wealth and captures the effect of household wealth on children's school achievement.

ix Highest grade completed: To capture the effect of schooling on educational achievement (measured by test scores), the highest grade completed by the child is used. Furthermore, we have omitted the enrolment dummy as most of the children in the sample (about 90 per cent) were enrolled in school in 2009 and this did not show the effect of schooling fully. However, the effect of those who had dropped out, enrolled late and attended school irregularly is captured by their highest grade completed. And it is the highest grade completed by the child that can fully capture the effects of schooling on the test outcomes.

x Locality: This is a dummy variable for urban included as an instrument for child work. Since the local wage rate we have in our dataset has a lot of missing values, we used locality a proxy for local wage rates and hence as an instrument for child work.

xi Household's experience of shocks: The dummy variables for a household's experience of drought and crop failure, and a household's experience of increases in the price of foods in the last four years are included in the regressions as instrumental variables for child work. These variables were measured in Round 3.

4.3 Descriptive statistics

In Young Lives the educational achievement of children is measured by a number of numeracy, literacy and mathematical tests. The PPVT is a receptive vocabulary test intended to provide immediate estimates of children's verbal ability and scholastic aptitude. The test requires respondents to select the pictures that best represent the meaning of a series of stimulus words read out by the examiner. The PPVT consists of 17 sets of 12 words each and the raw scores can take values from 0 to 204. In this paper the raw PPVT scores in Round 3 were taken to measure and compare the educational achievement of children.
As can be observed from Table 1 the average raw PPVT score was found to be higher for boys than for girls. We see that the raw PPVT scores of girls were lower by about 4 percentage points than those of their male counterparts.

Table 1. *Average raw PPVT scores of boys and girls at the age of 15*

Gender	PPVT score	
	N.	Mean
Girl	476	149.88
Boy	492	153.87
Total	968	151.91

Source: Own computation based on Young Lives R3 Older Cohort data.

The average raw PPVT scores of the children were found to be higher for urban children than for rural ones (Table 2). There was a difference of about 30 mean percentage points between the two groups.

Table 2. *Average raw PPVT scores of urban and rural children at the age of 15*

Location	PPVT score	
	N.	Mean
Rural	579	139.48
Urban	389	170.41
Total	968	151.91

Source: Own computation based on Young Lives R3 Older Cohort data.

Table 3 presents the average raw PPVT scores of children disaggregated according to the gender of the head of household. The average raw scores of children living in female-headed households are lower than those of children living in male-headed households (Table 3).

Table 3. *Average raw PPVT scores of children in male-headed and female-headed households at age 15*

Gender of head of the household	PPVT score	
	N.	Mean
Female head	737	149.21
Male head	231	160.53
Total	968	151.91

Source: Own computation based on Young Lives R3 Older Cohort data.

The differences in the average raw scores of children depending on the region they live in is presented in Table 4. The average raw PPVT score was the highest for Addis Ababa followed by Tigray and SNNPR. The lowest average raw score was recorded for children living in the Amhara region. These results may be due to the regions' different rates of urbanisation, as well as some aspects of educational quality. For instance, the 2007 population census reported that Tigray contained about 20 per cent of Ethiopia's urban population, which is higher than the country average of 16 per cent; whereas Amhara, Oromia and SNNP regions had 13, 12 and 10 per cent respectively. In terms of educational quality, the pupil–section ratio (number of pupils per section) and pupil–teacher ratio were lower for Tigray as compared to the other three regions covered by Young Lives (Amhara, Oromia and SNNP). Besides, low grade-repetition and drop-out rates and high completion rates were also observed in Tigray (MOE 2013).

Table 4. *Average raw scores of children living in different regions at age 15*

Region	PPVT score	
	N.	Mean
Addis Ababa	141	174.9
Amhara	189	138.69
Oromia	197	146.82
SNNPR	241	148.37
Tigray	200	157.47
Total	968	151.91

Source: Own computation based on Young Lives R3 Older Cohort data.

As can be observed in Table 5 the average raw scores of children who have engaged in all forms of child work are lower than those of the children who have not.

Table 5. *Average raw PPVT scores by child work at age 15*

Child participation	PPVT score			
	No		Yes	
	N	Mean	N	Mean
Child care	538	156.67	430	145.95
Household chores	88	152.64	880	151.84
Unpaid family business	581	157.82	387	143.04
Paid activities	885	152.83	83	142.12

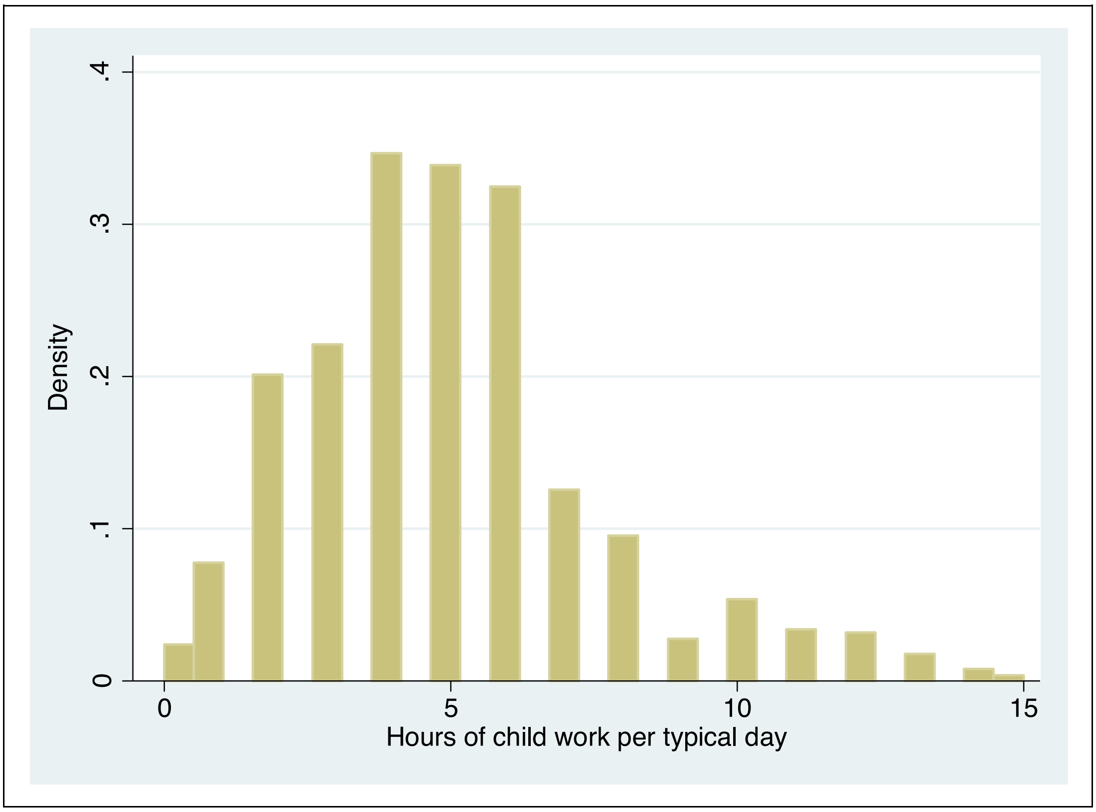
Source: Own computation based on Young Lives R3 Older Cohort data.

We generated a variable for child labour using a two-hours-work-per-day threshold to see the proportion of children working above and below the threshold. We can deduce from Table 6 that only about 15 per cent of the children in the sample were working for two hours or fewer whereas about 85 per cent of the children were engaged in child labour (that is, they were working for more than two hours per day). Hence, we can see that there is no significant difference between child work and child labour, as most of the children were involved in child labour.

Table 6. *Proportion of child work and child labour at age 15*

Region	PPVT score	
	N.	Mean
Work more than 2 hours per day	816	84.30
Work 2 hours or fewer	152	15.70

Figure 1: *Histogram for hours of child work*



The average hours different groups of children spent working per typical day is summarised in Table 7. In the first part the mean hours of work of children engaging in different activities is summarised; the second part presents the average hours of work for the whole sample. The proportion of children engaging in household chores was the highest (at 90 per cent) followed by those doing child-care activities (44 per cent) and unpaid family business work (40 per cent). However, small proportions of children (about 9 per cent) were engaged in paid activities. As regards the mean hours of work, considering only the sample of children who participated in the respective activities, the mean hours of work are highest for those children engaging in paid activities (4.795 hours), followed by unpaid family business activities (3.346 hours). The average hours of work of children who participated in household chores and child care were about 2.9 hours and 1.6 hours respectively. On the other hand, if the whole sample is considered, the activity that consumed the highest average hours of work was household chores and the one with the lowest average was paid activities. This is due to the fact that children engaged in household chores constitute the highest proportion while children in paid activities the lowest proportion.

Table 7. *Average hours of child work per day at age 15 by activity*

Activity	Proportion of children engaging (%)	Participating sample		Whole sample	
		N.	Average hours of work per day	N.	Average hours of work per day
Child care	43.97	430	1.565	978	0.698
HH chores	89.98	880	2.861	978	2.589
Unpaid family business	39.57	387	3.346	978	1.346
Paid activities	8.49	83	4.795	978	0.417

Source: Own computation based on Young Lives R3 Older Cohort data.

The extent of household shocks is also summarised. Table 8 shows that 85 per cent of the households in the sample reported that they had experienced increases in the price of foods they bought in the previous four years. This was even worse for urban areas, where 97 per cent of the households were hit by a shock caused by increases in the price of food. On the other hand, 53 per cent of the households in the sample had experienced drought, crop failure and pests and diseases in the last four years. In rural areas 76 per cent of the households faced this shock whereas it was very low in urban areas. So we can see that significant numbers of households were affected by occurrences of different shocks, especially by these two shocks.

Table 8. *Price and crop failure shocks in the last four years*

Increases in the price of foods				Drought, crop failure and pests			
	Rural	Urban	Overall		Rural	Urban	Overall
No	23.14	2.83	14.98	No	24.01	80.72	46.8
Yes	76.86	97.17	85.02	Yes	75.99	19.28	53.2
Total cases	579	389	968	Total cases	579	389	968

Source: Own computation based on Young Lives R3 Older Cohort data.

5. Estimation results, discussion and robustness check

In this section, the results of the various estimations will be discussed. It includes both OLS and two-stage least square regressions in which households' localities and experiences of socio-economic shocks were used as instruments for child work to deal with its endogeneity. Besides, to capture the effect of past cognitive ability on current test scores, the previous test scores of children were also included as an explanatory variable in estimating the effect of child work on the test scores. The sample used in regressions included both children who were enrolled in school and those who were not enrolled. To capture the effect of schooling on educational achievement, the highest grade completed was used in the estimation because even if attending school, pupils of the same age may not be in the same grade and an enrolment dummy may not fully capture the effects of schooling on the test scores; rather we thought it was the highest grade completed by the child that captured the effects of schooling on the test scores of children. This is because the majority of the children in the sample were attending school in 2009 and we could not control for those who had dropped out temporarily or permanently. Hence, the highest grade completed by the child was used as an explanatory variable to capture the effects of schooling on the test scores.

The dependent variable is the log of a child's raw PPVT score in the Round 3 data. Different diagnostic tests were also conducted to check for endogeneity in child work, to check the existence of weak instruments and for an over-identification problem. The following sub-sections will discuss the results of these regressions.

5.1. Estimation results

In order to explore the effect of child work on children's receptive vocabulary, a set of OLS and IV regressions were run. The estimates from OLS are a useful reference point for the subsequent IV results even though they are not believed to be causal. IV estimation allows one to interpret the results as causal but due attention should be given to the weak instrument problem. Three instruments were used in the estimation of the effect of child work on educational achievement.

From the first-stage regression, presented in Table 9, the first instrument, dummy for drought crop failure and pests and diseases, is also individually significant and strongly correlated with child work in the raw PPVT scores. The second instrument, dummy for increases in the price of food, is also individually significant and has a strong correlation with child work. Similarly, the third instrument, urban dummy, is also individually significant at the 1 per cent level and is strongly correlated with child work. This implies that all of the instruments are valid and child work is endogenous. Furthermore, the joint significance of the instruments was also reported in the first-stage results of 'ivreg2' estimation. The results reveal that the null hypothesis that 'all the coefficients of the instruments are zero' was rejected at the 1 per cent level of significance, implying an optimal combination of the instruments. This result confirms that the OLS results are significantly different from the IV approach and therefore child work is endogenous and the OLS estimates are biased (see Table 9).

Table 9. *First-stage regression of child work on the exogenous explanatory variables and instruments*

	Child work at time *t* **coef/t**
Log of raw PPVT score at time *t-1* or in Round 2	-0.112 (-0.394)
Highest grade completed R3	-0.349*** (-5.845)
Age (months)	0.035 (1.609)
Number of male family members less than or equal to 7 years old R3	0.106 (0.911)
Number of male family members between age 7 and 17 R3	0.096 (1.068)
Number of male family members > 17 and less than 65 years R3	0.040 (0.729)
Number of male family members > =65 years R3	0.340* (1.743)
Number of female family members less than or equal to 7 years old R3	0.188* (1.916)
Number of female family members between age 7 and 17 R3	0.100 (1.152)
Number of female family members > 17 and less than 65 years R3	-0.073 (-1.017)
Number of female family members > =65 years R3	0.007 (0.026)
Dummy for male child	-0.331 (-1.256)
Father's education level	0.014** (2.080)
Mother's education level	-0.006 (-0.776)
Dummy for male household head	0.102 (0.649)
Wealth Index– Round 3	-1.155* (-1.925)
Dummy for drought crop failure and pests and diseases	0.616*** (2.626)
Dummy for increases in the price of food	0.345** (2.136)
Dummy for urban residence	-0.907*** (-2.747)
Constant	0.971 (0.239)
Number of observations	886
Adjusted R2	0.267

Robust standard errors clustered at the sentinel site level
*** p<0.01, ** p<0.05, * p<0.1; t-values in parentheses
R2=Round 2; R3=Round 3
Tests of joint significance of endogenous regressors B1 in main equation
Ho: B1=0 and over-identifying restrictions are valid
Anderson-Rubin Wald test F(3,20)= 8.06 P-val=0.0010
Anderson-Rubin Wald test Chi-sq(3)=25.95 P-val=0.0000
Stock-Wright LM S statistic Chi-sq(3)=12.18 P-val=0.0068

Table 10 presents the effect of child work on the log of raw PPVT scores of 15-year-old children using both the OLS and the instrumental variable regressions. It shows that the child work variable was found to have a statistically significant effect on the raw PPVT scores at the 5 per cent level of significance. This implies that an increase in the number of hours worked per day by 1 will result in a reduction in the raw PPVT scores of a child by 6.2 per cent.

The PPVT score of a child in the previous round was found to have a significant effect on the PPVT score of that child at the 1 per cent level of significance, implying that an increase in the raw PPVT score in Round 2 by 1 per cent leads to an increase in the raw scores of a child in Round 3 by 0.11 per cent. All of our household composition variables were found to have a statistically insignificant effect on the raw PPVT scores of children except the number of male family members between the ages of 17 and 65 and above the age of 65, at the 10 per cent and 1 per cent levels of significance respectively; and the number of female family members between the ages of 17 and 65 at the 10 per cent level of significance. The results may suggest that as the household has more labour available, especially male members of age 17 and above, the better children do in school. These results may be due to the fact that the work is shared among the household members and probably children have to work fewer hours.

In addition, the male household head dummy and the wealth index were also found to have a positive significant effect on the log of raw PPVT scores of children at the 1 per cent and 10 per cent levels of significance respectively; implying that children from male-headed households performed 6.3 per cent higher in the PPVT than those from than female-headed households and as the wealth index increases by 1, the raw PPVT scores of children increase by 16.6 per cent. Furthermore, even though not causal, the OLS estimation reveals that the highest grade completed and the male child dummy were found to have positive significant effects at the 5 per cent and 10 per cent levels of significance respectively.

Table 10. *OLS and IV estimation of log of PPVT scores in Round 3: Effect of child work on school achievement (PPVT)*

	OLS coef/t	IV coef/t
Hours of child work per typical day	-0.005 (-1.175)	-0.062** (-2.115)
Log of raw PPVT score in R2	0.139*** (3.080)	0.114** (2.419)
Highest grade completed	0.041*** (7.206)	0.019 (1.479)
Age (months)	0.001 (0.458)	0.002 (0.885)
Number of male family members less than or equal to 7 years old R3	-0.006 (-0.538)	0.001 (0.070)
Number of male family members between age 7 and 17 R3	-0.007 (-0.886)	0.004 (0.348)
Number of male family members > 17 and less than 65 years R3	0.010* (1.676)	0.014* (1.885)
Number of male family members > =65 years R3	0.052** (2.184)	0.072*** (2.675)
Number of female family members less than or equal to 7 years old R3	-0.006 (-0.797)	0.007 (0.740)
Number of female family members between age 7 and 17 R3	0.003 (0.216)	0.012 (0.703)
Number of female family members > 17 and less than 65 years R3	-0.008 (-1.402)	-0.012* (-1.903)
Number of female family members > =65 years R3	0.021 (0.883)	0.023 (0.848)
Dummy for male child	0.052* (1.877)	0.031 (1.046)
Father's education level	0.000 (0.397)	0.002 (1.463)
Mother's education level	0.000 (0.482)	-0.000 (-0.155)
Dummy for male household head	0.063*** (3.109)	0.063*** (2.905)
Wealth Index – Round 3	0.339*** (4.367)	0.166* (1.730)
Constant	3.783*** (8.080)	4.076*** (8.518)
Number of observations	886	886
Adjusted R2	0.315	0.106
Centered R-squared, 1-rss/yyc (r2c)		0.123
Uncentered R-squared, 1-rss/yy (r2u)		0.997
LM test statistic for under-identification (Anderson or Kleibergen-Paap)		12.184
p-value of under-identification LM statistic (idp)		0.007
Hansen J statistic (j)		2.244
P-value of Hansen J statistic (jp)		0.326

Robust standard errors clustered at the sentinel site level

*** p<0.01, ** p<0.05, * p<0.1; t-value in parentheses

R2=Round 2; R3=Round 3; Endogenous variable= Hours of child work per typical day; Instruments= dummy for urban residence, dummy for drought, crop failure and pest and diseases, and dummy for the increase in the prices of foods in the last four years.

5.2. Discussion and checking for robustness

The results of the estimations made showed that child work had a negative effect on the raw PPVT scores of children but was insignificant in the OLS estimation, which could be due to the fact that child work is endogenous and OLS bias is positive, suggesting that there are unobserved factors positively correlated with child work and cognitive achievement. However, one can infer that there is clear causal evidence that child work has an adverse impact on the educational attainment of children.

In line with the findings of the current study, Beegle et al. (2009), considering only rural households, investigated the long-term impact of child labour on grade attainment and participation in Vietnam, and they found a negative impact of child labour on educational outcomes, though they did not take test scores as education outcomes. Gunnarson et al. (2006) also estimated by pooling rural and urban households across nine countries and found that child work had a negative effect on educational outcomes. Further, Mavrokonstantis (2011) explored the causal evidence that child labour had a large adverse impact on educational attainment for children in urban areas but was insignificant for children in rural areas. Though our estimation has pooled the urban and rural children, our finding is comparable with their findings for urban children.

In contrast, Watson (2008) using different shock variables that were experienced both at the household and community levels as an instrument for child labour found that child labour did not have an effect on schooling outcomes. Bezerra et al. (2009) found that working children were found to have lower outcomes with children of the same age in Brazil; in contrast to our study, however, child work for up to two hours per day was not found to have a statistically significant effect and only child work beyond two hours per day was found to have a negative effect on schooling outcomes. But in the current paper, analysing the effect of child work beyond two hours (officially referred to as child labour) on the test scores did not bring different results because almost all the children in the sample worked for more than two hours a day and hence no significance difference was observed. Due to this only the results of child work, for all children working less than and more than two hours per day, are discussed and presented in the current paper as both child work and child labour are comparable.

The IV regression in this study has been subjected to a number of robustness tests, specifically under-identification, weak identification and over-identification tests. The ‘ivreg2’ command in Stata provides extensions to Stata’s official IV regression and automatically reports all the above robustness tests.

Table 11 presents the results of robustness tests for the raw PPVT scores. The under-identification test is an LM (Lagrang multiplier) test of whether the equation is identified, i.e., the excluded instruments are relevant, meaning correlated with the endogenous regressors. From the ‘ivreg2’ results we found that the null hypothesis of under-identification was rejected in the log of raw PPVT scores, indicating that the model was identified. When the excluded instruments are weakly correlated with the endogenous variable it leads to the problem of weak identification. The test for weak identification automatically reported by ‘ivreg2’ is an F version of the Cragg-Donald Wald statistic. Stock and Yogo (2005) have compiled critical values for the Cragg-Donald F statistic for several different estimators. However, when the i.i.d (identically and independently distributed) assumption is dropped and ‘ivreg2’ is invoked with the robust, cluster options, the Cragg-Donald-based weak instruments test is no longer valid. ‘ivreg2’ instead reports a correspondingly robust Kleibergen-Paap Wald rk F statistic. The critical values reported by ‘ivreg2’ for the Kleibergen-Paap statistic are, however, the

Stock-Yogo critical values for the Cragg-Donald i.i.d. case. Table 11 shows that the Kleibergen-Paap statistic is greater than 10 for the PPVT regression, which indicates that the estimation is not weakly identified. And finally the 'ivreg2' command in Stata also provided the over-identification test automatically which are pseudo-F versions of Sargan's statistic. From Table 11, we can infer that our estimations do not suffer from the over-identification problem. This confirms the statistical validity of the instruments and implies an optimal combination of instruments.

Table 11. *Robustness tests*

PPVT	
Under-identification test (Kleibergen-Paap rk LM statistic)	15.117
Chi-sq(3) P-val =	0.0017
Weak identification test (Kleibergen-Paap rk Wald F statistic)	10.023
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias	13.91
10% maximal IV relative bias	9.08
20% maximal IV relative bias	6.46
30% maximal IV relative bias	5.39
10% maximal IV size	22.3
15% maximal IV size	12.83
20% maximal IV size	9.54
25% maximal IV size	7.8
Hansen J statistic (over-identification test of all instruments):	2.244
Chi-sq(2) P-val =	0.3256

6. Conclusion

Given the importance of education for the future earnings of children and the human capital accumulation at the country level, it is necessary to identify the factors that determine the educational achievement of children. Child work is one of the factors that affects education, by taking away children's time and energy from school and school-related work. It is, therefore, crucial to look into the relationship between the two variables to identify points for policy intervention. To this end, this study explored the effect of child work on children's school achievement measured using their raw scores in the PPVT.

Recognising the simultaneous relationship between child work and education, which results from the fact that opportunity costs of the child's time affect both child work and education, an IV method was used in addition to OLS to identify the effect of child work on children's achievement.

The results of the estimations made showed that child work had a negative effect on children's raw PPVT scores. Hence, there is clear causal evidence that child work has an adverse impact on children's educational attainment. Overall, child work exhibited a negative effect on children's educational achievement, as measured by receptive vocabulary test scores. Therefore, it is necessary for the Government of Ethiopia to intervene by dealing with the factors that trigger children to work. They need to design programmes that would increase the income of households, so that children would not be required to work so much.

One such solution could be to introduce a cash transfer programme conditional on children attending school. This would raise household income as well as potentially increasing children's future earning capacity. In addition, providing households with incentives to make their children attend school instead of having them spend their time on paid and unpaid work would perhaps enable children to spend more of their free time studying. Learning from the experiences of Latin America, social protection should also help households cope with the different kinds of shock. Moreover, increasing access to credit could be an additional way of empowering households to withstand some of the income shocks that lead to increased child work.

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Appendix

Table A1. *Summary statistics of variables on the regression*

	N	Mean	Min	Max
Log of raw PPVT score R3	968	4.990	1.946	5.313
Log of raw PPVT score R2	953	4.780	3.091	5.298
Hours worked per day R3	970	5.053	0	15.00
Grade completed	975	5.505	0	11
Age (months)	974	180.3593	169.5452	192.2301
Number of boys below 7 years R3	968	0.441	0	3
Number of boys between 7 and 17 years R3	968	1.389	0	5
Number of male household members between 17 and 65 years R3	968	2.001	0	8
Number of male elderly above 65 R3	968	0.101	0	1
Number of girls below 7 years R3	968	0.483	0	3
Number of girls between 7 and 17 years R3	968	1.365	0	5
Number of female household members between 17 and 65 years R3	968	2.233	0	10
Number of female elderly above 65 R3	968	0.103	0	2
Dummy for boy child R3	968	0.508	0	1.00
Dummy for urban household R3	968	0.402	0	1.00
Education level of father	905	9.737	0	29.00
Education level of mother	955	5.977	0	29.00
Dummy for female head of household	968	0.239	0	1.00
Wealth index R3	968	0.3508966	0	0.861111
Dummy for drought crop failure and pests and diseases in the last 4 years	968	0.532	0	1
Increase in the prices of foods in the last 4 years R3	968	0.850	0	1

Source: Own computation based on Young Lives data.

Is Child Work Detrimental to the Educational Achievement of Children? Results from Young Lives in Ethiopia

The objective of this study is to explore the effect of child work on school achievement as measured by the Peabody Picture Vocabulary Test (PPVT). Identifying the causal effects of child work on education is made difficult because the choice of work and/or school is made simultaneously and may be determined by the same potentially unobserved factors. Therefore, both ordinary least square and instrumental variable estimation methods were used to identify the effect of child work on school achievement. We used dummy variables for drought, crop failure and pests and diseases, for increases in the prices of food, and for urban locality as instruments which are highly, though not directly, correlated with achievement in education. The results obtained showed that child work had a negative effect on child achievement in education as measured by the raw PPVT score. Therefore, it is important to design mechanisms that enable households to withstand income shocks without resorting to child work. The Government of Ethiopia should consider implementing a programme that provides financial incentives to households to send their children to school regularly, thus potentially increasing the children's future earning capacity. A conditional cash transfer programme could be a way of helping children achieve better in school and of minimising child work.

Young Lives
An International Study of Childhood Poverty

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About Young Lives

Young Lives is an international study of childhood poverty, involving 12,000 children in 4 countries over 15 years. It is led by a team in the Department of International Development at the University of Oxford in association with research and policy partners in the 4 study countries: Ethiopia, India, Peru and Vietnam.

Through researching different aspects of children's lives, we seek to improve policies and programmes for children.

Young Lives Partners

Young Lives is coordinated by a small team based at the University of Oxford, led by Professor Jo Boyden.

- *Ethiopian Development Research Institute, Ethiopia*
- *Pankhurst Development Research and Consulting plc, Ethiopia*
- *Save the Children (Ethiopia programme)*
- *Centre for Economic and Social Studies, Hyderabad, India*
- *Save the Children India*
- *Sri Padmavathi Mahila Visvavidyalayam (Women's University), Andhra Pradesh, India*
- *Grupo de Análisis para el Desarollo (GRADE), Peru*
- *Instituto de Investigación Nutricional, Peru*
- *Centre for Analysis and Forecasting, Vietnamese Academy of Social Sciences, Vietnam*
- *General Statistics Office, Vietnam*
- *Oxford Department of International Development, University of Oxford, UK*

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