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

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Abstract

The objective of this study was to explore the effect of child work on educational 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 schooling is made simultaneously and may be determined by the same potentially unobserved factors. Therefore, both Ordinary Least Square (OLS) and Instrumental Variable (IV) estimation methods were used to identify the effect of child work on educational 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. Numerically, an increase in the number of hours worked per day by one resulted in a reduction in the PPVT score of a child by 6.2 percent. Therefore, it is important to design mechanisms that enable households to withstand income shocks without resorting to child work. The Government of Ethiopia might need to consider implementing a programme that provides financial incentives to households to send their children to school regularly, thus potentially increasing their educational achievement.

Key words: child work, educational achievement, PPVT, Young Lives, Ethiopia
JEL Codes: J22, D63, I38 & C30

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1. Introduction

Parents have the discretion over the allocation of their children's time to different activities such as schooling and work. 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 them to school, while the second reason 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 enroll 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 children's time in school with the expectation of higher future earnings (Brown and Park, 2002).

The Ethiopian Government has been directing its resources to achieving the second Millennium Development Goals of universal primary education. Moreover, it has 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 policy makers.

The literature on the relationship between child work and education shows that the results are mixed. Most found offsetting relationships between the two (e.g. Bezerra *et al.*, 2009; Heady, 2000; Rosati and Rossi, 2001; Gunnarson e*t al.*, 2006), while some other studies reported complementing relationships between child work and education (Ravallion and Wodon, 2000; Patrinos and Psacharopoulos, 1997) and some others found no significant relationships (Watson, 2008; Mavrokonstantis, 2011 for rural areas). The current paper will, therefore, add value to the ongoing debate. Moreover, although several studies have been conducted in other developing countries, only a few have been carried out in Ethiopia to explore the relationship between child work and education. And of the few that have been done, most don't deal with the endogenous nature of child work. For example, two studies that explored the relationship between child labour and education were conducted by Young Lives. The first is by 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 is also from Woldehanna and Hagos (2012), which explored the effect of economic shocks on children dropping out of primary school, using an accelerated failure-time hazard model. 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. This study, thus, 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 is believed to improve the reliability of the evidence to be used for policy making. In addition to dealing with simultaneity, this study makes use of Peabody Picture Vocabulary Test (PPVT) as educational achievement rather than more commonly used measures such as enrolment rates and primary school completion rates. Such an educational measurement is believed to assess the effect of child work on the cognitive development of children as the data contains cores for all children in the sample of the Young Lives study. And this makes the study unique as most of the studies on child work[4] 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 was to investigate the causal effect of child work on real education achievement as measured by PPVT scores.

[4] In this study, the term 'child work' refers 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.

However, it is worth noting that when one tries to investigate how child work affects schooling, 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, that is 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 effects of child work on educational attainment are established (Ravallion and Wodon, 2000). To this effect, the study uses Round 2 and Round 3 data collected in Ethiopia in 2006 and 2009, respectively, by Young Lives, which has compiled a unique panel data set on children's welfare and their families' livelihoods. The data used are from the Older Cohort (born in 1994/95) because most of the children in the Younger Cohort (born 2001/02) were not enrolled in school in Round 2 (2006). Moreover, the children of the younger cohort were enrolled in lower grades in Round 3.

Regarding the methods of analysis, the study used 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 was used to explore the causal effect child work had on education. A sensitivity analysis was also conducted to check for the robustness of the results. Findings showed that child work is one of the factors that affect negatively the educational achievement of children, by taking away their time and energy from school and school-related tasks. More specifically, estimation result from the IV regression showed that PPVT score of a child declines by about 6.2 percent if the number of hours worked per day increases by 1. This implies that child work is detrimental to children's educational achievement.

The remaining parts of the paper are organized as follows. In Section 2 the review of literature is presented, while Section 3 specifies the theoretical and empirical models employed in the analysis. Section 4 reports the results. Section 5 concludes with some remarks.

2. Review of Literature

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.[5] Based on this conceptual framework, several studies have been carried out to examine the effect of child work/labour on schooling. For example, 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 analyzed 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 child labour and school were mutually exclusive in Peru. Furthermore, authors 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 examine whether there was a causal relationship between the two variables using IV methods to deal with the endogenous nature of child labour. The results are, however, mixed. After instrumenting child labour

[5] 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.

with crop shocks experienced at 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.

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, whereas children who did not work were found to have 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 he 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.

3. Model Specification

3.1 Theoretical model

We start with the education production function as discussed in Gunnarsson and Orazem (2003), where 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 assumed to be a function of child work status, household, school and community-level factors, and previous level of educational achievement or test scores. We can specify this educational production function as:

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

where H_{ijt} is test scores, C_{ijt} 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 formula:

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

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, Y is non-labour income earned by the household, and Z is a vector of dummy variables for a household's experience of shocks in the last four year.

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 explanatory 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 (Beegle *et al.,* 2006; Ravallion and Wodon, 2000). 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. 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 data set from a single country, we cannot make use of inter-country differences as an instrument for child labour, as in Gunnarsson *et al.* (2006). Nor 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 data set. 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 Watson (2008) and Beegle *et al.* (2003), this study used the incidences of drought, crop failure and pests, and disease shocks the household faced 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 crops 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 instrument in her study, were highly and significantly correlated with child labour, and she remarked that these shock instruments were successful. 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 variable 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 food 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 percent of households in our sample reported that they had faced a food price increase and our study explored 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 good candidate for an instrument. Usually urban wage rates are higher than rural wages in the slack seasons where there are no intensive agricultural activities, while rural wages vary across seasons. During the peak agricultural seasons, rural wages rise but are 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 data set 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 PPVT 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 empirical model used for the estimation is:

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

where H_{ijt} is children's educational achievement, as measured by the 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:

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

where C is the number of hours a child spends working per day, Z is a vector of dummy variables for a household's experience of shocks in the last four years, and G is a control for locality that controls for local wages proxied by urban dummy. 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.

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[6], the two-hour-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 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 percent 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 of 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.

3.2 Data

This study utilized 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, but by Round 3, they were also enrolled in lower grades. The sample contains 970 children who live in 20 sentinel sites located in five of the regions in the country, namely Addis Ababa, Oromia,

[6] 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).

Amhara, SNNPR and Tigray. These regions were selected because 96 percent 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 percent of the sentinel sites in each region were selected from high food-deficit woredas (districts) while 25 percent were selected from a lower food-deficit woreda. The children in the rural areas comprise 60 percent of the sample while 40 percent are from urban areas. Each region comprises 20 percent of the total sample, except for Addis Ababa, which contains 15 percent of the sample and SNNPR, where 25 percent of the sample was selected from. Data on population density were also taken into account when sentinel sites were selected. Moreover, consultations were held with regional policy makers and other stakeholders. Within each sentinel site, a simple random sample of 100 households was taken.

Regarding child work, we generated the data from the sum of hours spent per typical day in the previous week of the Round 3 survey, which includes doing domestic tasks, caring for others, 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 care giver. This 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 were 5.05 and those given by the care giver were 4.95, with a range for both information between 0 and 15. In terms of educational achievement, we used the scores in the Peabody Picture Vocabulary Test (PPVT). This PPVT is captive 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 study, the raw PPVT scores in Round 3 were taken to measure and compare the educational achievement of children instead of the highest grade they completed. We also applied log transformation for the PPVT scores to simplify interpretation.

4. Results

4.1 Descriptive statistics

Descriptive results of the PPVT score are presented in Table 1 in groups. Preliminary results show that the average PPVT score was higher for boys than for girls, with a difference of about 4 mean points. The average scores of children living in male-headed households were also significantly higher than those living in female-headed households. The same is true for urban children who scored 30 mean points larger than children living in rural areas. There are also considerable disparities by regional location, where the score gap was, on average, as large as 36.21 between children living in Addis Ababa and those residing in the Amhara region.

Table 1: Average raw PPVT scores of children at age 15, by group

	No.	PPVT score (out
Gender of child		
Boy	492	153.87
Girl	476	149.88
Gap		3.98*
Gender of household head		
Male	231	160.53
Female	737	149.21
Gap		11.32***
Residence area		
Urban	389	170.41
Rural	579	139.48
Gap		30.93***
Regional location		
Addis Ababa	141	174.9
Amhara	189	138.69
Oromia	197	146.82
SNNP	241	148.37
Tigray	200	157.47
Gaps (max)		36.21***

Source: Own computation based on Young Lives R3 Older Cohort data
Statistically significant at*** p<0.01, ** p<0.05, * p<0.1

In terms of working hours, the majority of the children participated in some work activities, up to 15 hours of work per day (Table A2). However, to have clear information on the working status, we generated a variable for child labour using a two-hour-work-per-day threshold to see the proportion of children working above and below this level. It appears that only about 15 percent of the children in the sample were working for two hours or fewer whereas about 85 percent of the children were engaged in child labour (Table 2). From this we can deduce that there is no significant difference between child work and child labour in this study as most of the children were involved in child labour.

Table 2: Proportion of child work and child labour at age 15

	N	Percentage
Work more than 2 hours per day	816	84.30
Work 2 hours or fewer	152	15.70

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

By type of work activity, the proportion of children engaging in household chores was the highest (90 percent), followed by those doing child-care activities (44 percent) and unpaid family business work (40 percent) (Table 3). However, small proportions of children (about 9 percent) 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 (4.8 hours), followed by unpaid family business activities (3.4 hours). The average hours of work of children who participated in household chores and child care were, however, relatively low, with about 2.9 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 make up the lowest proportion.

Table 3: 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
Child care	43.97	430	1.56	978	0.69
HH chores	89.98	880	2.86	978	2.58
Unpaid family	39.57	387	3.34	978	1.34
Paid activities	8.49	83	4.79	978	0.41

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

It is also important to have a look at the educational achievement of the children in relation to work participation. As can be seen in Table 4, 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, and this was statistically significant except in household chores.

Table 4: Average raw PPVT scores by child work at age 15

Child participation	PPVT		
	No	Yes	Gap
Child care	156.67	145.95	10.71**
Household chores	152.64	151.84	0.801
Unpaid family business	157.82	143.04	14.78***
Paid activities	152.83	142.12	10.70***

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

Also, the extent of household economic shocks that are used as instruments for child work are summarized in Table 5. It seems that about 85 percent of the households in the sample experienced an increase in the price of food in the previous four years of the survey. This was even worse for urban areas, where 97 percent of the households were hit by food price hicks. On the other hand, 53 percent of the households in the sample had experienced drought, crop failure and pests, and diseases. In rural areas, 76 percent of the households faced this shock whereas the shock was very low in urban areas. So we can see that significant numbers of households were affected by occurrences of different shocks, especially by price and crop failure shocks.

Table 5: 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.

4.2 Estimation Results

In this section regression results are discussed. It includes both OLS and two-stage least square regressions in which households' localities and experiences of 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, previous test scores were also included as an explanatory variable in estimating the effect of child work on current test scores. The sample used in regressions included both children who were enrolled in school and those who were not enrolled. To control for the effect of schooling on educational achievement, the highest grade completed was used in the estimation because, even when 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 PPVT scores; rather, we thought it was the highest grade completed by the child that captured the effects of schooling on the test scores. 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.

Before dealing with the estimates, it is imperative to have a look at the first-stage regression of the IV approach and examine whether the selected instruments are valid. Table A2 presents the result of this regression. It appears that all the instruments - dummy for drought, crop failure and pests and diseases, dummy for increases in the price of food, and urban dummy are individually significant and strongly correlated with child work in the PPVT scores. Furthermore, the joint significance of the instruments was reported in the first-stage estimation results. The results reveal that the null hypothesis that 'all the coefficients of the instruments are zero' was rejected at the 1 percent level of significance, implying an optimal combination of the instruments; therefore, child work is endogenous where OLS are significantly different from that of the IV approach.

Table 6 reports the estimation results. The estimates from OLS are a useful reference point for the subsequent IV results even though they are not believed to because: l. the result from the IV estimation shows that child work was found to have a statistically significant negative effect on the PPVT scores at 5 percent level of significance. In other words, an increase in the number of hours worked per day by 1 will result in a reduction in the PPVT scores of a child by 6.2 percent. Regarding the control variables, the PPVT score of a child in the previous round was found to have a significant effect on the current PPVT score of that child at 1 percent level of significance, implying that being advantageous at one point of time results in a better educational achievement at a later time. In the literature, this is known as the Mathew Effect in that children with higher skills will tend to achieve higher scores than children with lower skills. Also, the male household head dummy and the wealth index were found to have a positive significant effect on the log of PPVT scores of children at 1 and 10 percent levels of significance, respectively. This is to mean that children from male-headed households performed 6.3 percent higher in the PPVT than those from female-headed households, and as the wealth index increases by 1, the PPVT scores of children increase by 16.6 percent. Furthermore, 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 percent and 10 percent levels of significance, respectively. Many of the other household composition variables were, however, found to have a statistically insignificant effect on the PPVT scores of children except for the number of male family members between the ages of 17 and 65, and above the age of 65, at the 10 percent and 1 percent levels of significance, respectively, and the number of female family members between the ages of 17 and 65 at 10 percent level of significance. The results may suggest that the more labour supply a household has especially male members of age 17 and above, the better children do in school. In other words, when workforce is larger in a given household, work can be shared among the household members, and probably children have to work fewer hours as the result.

Table 6: OLS & IV estimation of log of PPVT in Round 3: Effect of child work on educational achievement

	OLS: PPVT score	IV: PPVT score
	coef/t	coef/t
Hours of child work per typical day	-0.005	-0.062**
	(-1.175)	(-2.115)
Log of raw PPVT score in R2	0.139***	0.114**
	(3.080)	(2.419)
Highest grade completed	0.041***	0.019
	(7.206)	(1.479)
Age (months)	0.001	0.002
	(0.458)	(0.885)
Number of male family members less than or equal to 7 years old R3	-0.006	0.001
	(-0.538)	(0.070)
Number of male family members between age 7 and 17 R3	-0.007	0.004
	(-0.886)	(0.348)
Number of male family members > 17 and less than 65 years R3	0.010*	0.014*
	(1.676)	(1.885)
Number of male family members > =65 years R3	0.052**	0.072***
	(2.184)	(2.675)
Number of female family members less than or equal to 7 years old R3	-0.006	0.007
	(-0.797)	(0.740)
Number of female family members between age 7 and 17 R3	0.003	0.012
	(0.216)	(0.703)
Number of female family members > 17 and less than 65 years R3	-0.008	-0.012*
	(-1.402)	(-1.903)
Number of female family members > =65 years R3	0.021	0.023
	(0.883)	(0.848)
Dummy for male child	0.052*	0.031
	(1.877)	(1.046)
Father's education level	0.000	0.002
	(0.397)	(1.463)
Mother's education level	0.000	-0.000
	(0.482)	(-0.155)
Dummy for male household head	0.063***	0.063***
	(3.109)	(2.905)
Wealth Index – Round 3	0.339***	0.166*
	(4.367)	(1.730)
Constant	3.783***	4.076***
	(8.080)	(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.

4.3 Checking for robustness

The estimation results showed that child work had a negative effect on the PPVT scores of children though it 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, from the IV estimate, one can infer that there is clear causal evidence that child work has an adverse effect on the educational attainment of children. To check the rigorousness of this result, the IV regression was subjected to a number of robustness tests, specifically under-identification, weak identification, and over-identification tests.

Table 7 presents the results of these tests. The under-identification test is an LM (Lagrang Multiplier) test of whether the equation is identified, that is, whether the excluded instruments are relevant or correlated with the endogenous regressors. We found that the null hypothesis of under-identification was rejected in the log of 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 is an Fversion 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 invoked with the robust or cluster options, the Cragg-Donald-based weak instruments test is no longer valid. Instead a correspondingly robust Kleibergen-Paap Waldrk Fstatistic is reported. However, the critical values reported for the Kleibergen-Paap statistic are the Stock-Yogo critical values, which are the same as in the Cragg-Donald i.i.d. case. As can be seen, the Kleibergen-Paap statistic is greater than 10, which indicates that the estimation is not weakly identified. And, finally, the over-identification tests, which are pseudo-Fversions of Sargan's statistic, are reported. This test again signifies that our estimations do not suffer from the over-identification problem, confirming the statistical validity of the instruments.

Table 7: Robustness tests

PPVT	
Under-identification test (Kleibergen-Paaprk LM statistic)	15.117
Chi-sq(3) P-val =	0.0017
Weak identification test (Kleibergen-Paaprk 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

In addition to the statistical tests for the instruments, the main IV regression is estimated for the sample of children who work beyond 2 hours. For children, working more than two hours per day is labelled as child labour and is expected to affect child education more than the loose definition. If the results are robust and truly reflecting the effects of child labour, then we should find a higher and significant coefficient when we estimate against the restricted sample. To this end, we run the IV estimation on a sample of children who worked more than two hours per day. Table 8 presents the estimation results for the restricted sample. The result indicates that hours of child work negatively affect the PPVT score of children and the coefficient is higher than the one in Table 6, confirming the claim that the effect of child work is higher for children working more hours.

Table 8: IV estimation of log of PPVT in Round 3: Effect of child labour on educational achievement

Variables	(1) IV
Hours of child work per typical day	-0.0814*
Log of raw PPVT score in R2	0.130**
Highest grade completed	0.0188
	(0.0160)
Age (months)	0.00556*
	(0.00337)
Number of male family members less than or equal to 7 years old R3	0.00103
	(0.0139)
Number of male family members between age 7 and 17 R3	-0.000313
	(0.0120)
Number of male family members > 17 and less than 65 years R3	0.0191**
	(0.00745)
Number of male family members > =65 years R3	0.0888***
	(0.0316)
Number of female family members less than or equal to 7 years old R3	0.0116
	(0.00939)
Number of female family members between age 7 and 17 R3	0.00406
	(0.0190)
Number of female family members > 17 and less than 65 years R3	-0.0162*
	(0.00925)
Number of female family members > =65 years R3	0.0283
	(0.0362)
Dummy for male child	0.0478
	(0.0327)
Father's education level	0.0163
	(0.0247)
Mother's education level	-0.0274
	(0.0308)
Dummy for male household head	0.0796***
	(0.0235)
Wealth Index – Round 3	0.211**
	(0.0870)
Constant	3.571***
	(0.521)
Observations	746
R-squared	-0.001

Robust standard errors in parentheses clustered at sentinel site

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

5. 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 affect 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.

Recognizing 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 educational achievement. To do this, we used locality and household economic shocks experienced in the previous four years of the survey as instruments. Findings from the IV estimation showed that child work is detrimental to the educational achievement of children, 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. It is important to design programmes that would increase the income of households so that children would not be required to work so much. Providing households with incentives to make their children attend school instead of having them spend their time on paid and unpaid work activities 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 shocks. 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	4.9	1.95	5.31
Log of raw PPVT score R2	953	4.78	3.09	5.29
Hours worked per day R3	970	5.05	0	15.0
Grade completed	975	5.50	0	11
Age (months)	974	180.35	169.54	192.23
Number of boys below 7 years R3	968	0.44	0	3
Number of boys between 7 and 17 years R3	968	1.39	0	5
Number of male household members between 17 & 65 years R3	968	2.00	0	8
Number of male elderly above 65 R3	968	0.10	0	1
Number of girls below 7 years R3	968	0.48	0	3
Number of girls between 7 and 17 years R3	968	1.37	0	5
Number of female household members between 17 and 65 years R3	968	2.23	0	10
Number of female elderly above 65 R3	968	0.10	0	2
Dummy for boy child R3	968	0.51	0	1.00
Dummy for urban household R3	968	0.40	0	1.00
Education level of father	905	9.74	0	29.00
Education level of mother	955	5.98	0	29.00
Dummy for female head of household	968	0.24	0	1.00
Wealth index R3	968	0.35	0	0.86
Dummy for drought crop failure and pests & 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.

Table A2: 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 (Round2)	-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